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MODELING THE CONSUMER ACCEPTANCE OF RETAIL SERVICE ROBOTS

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I am submitting herewith a dissertation written by So Young Song entitled "MODELING THE CONSUMER ACCEPTANCE OF RETAIL SERVICE ROBOTS." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Retail, Hospitality, and Tourism Management.

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MODELING THE CONSUMER ACCEPTANCE OF RETAIL SERVICE ROBOTS

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DEDICATION

To my loving husband

Woong Yeol Joe

I dedicate my dissertation to my husband, Woong Yeol, and my precious children, Anna and Adam. I also dedicate this work to my parents and my in-laws. I will always appreciate all of you for being there for me and for praying with me throughout the entire doctorate program. Anna and Adam, both of you have made me smile and have been my best cheerleaders. Woong Yeol, I could not have done it without you. I am so thankful for your support and devotion.

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ABSTRACT

This study uses the Computers Are Social Actors (CASA) and domestication theories as the underlying framework of an acceptance model of retail service robots (RSRs). The model illustrates the relationships among facilitators, attitudes toward Human-Robot Interaction (HRI), anxiety toward robots, anticipated service quality, and the acceptance of RSRs. Specifically, the researcher investigates the extent to which the facilitators of usefulness, social capability, the appearance of RSRs, and the attitudes toward HRI affect acceptance and increase the anticipation of service quality. The researcher also tests the inhibiting role of pre-existing anxiety toward robots on the relationship between these facilitators and attitudes toward HRI. The study uses four methodological strategies: (1) incorporating a focus group and personal interviews, (2) using a presentation method of video clip stimuli, (3) empirical data collection and multigroup SEM analyses, and (4) applying three key product categories for the model's generalization—fashion, technology (mobile phone), and food service (restaurant). The researcher conducts two pretests to check the survey items and to select the video clips. The researcher conducts the main test using an online survey of US consumer panelists (n = 1424) at a marketing agency.

The results show that usefulness, social capability, and the appearance of a RSR positively influence the attitudes toward HRI. The attitudes toward HRI predict greater anticipation of service quality and the acceptance of the RSRs. The expected quality of service tends to enhance the acceptance. The relationship between social capability and attitudes toward HRI is weaker when the anxiety toward robots is higher. However, when the anxiety is higher, the relationship between appearance and the attitudes toward HRI is stronger than those with low anxiety.

This study contributes to the literature on the CASA and domestication theories and to

the human-computer interaction that involves robots or artificial intelligence. By considering social capability, humanness, intelligence, and the appearance of robots, this model of RSR acceptance can provide new insights into the psychological, social, and behavioral principles that guide the commercialization of robots. Further, this acceptance model could help retailers and marketers formulate strategies for effective HRI and RSR adoption in their businesses.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I
INTRODUCTION

Robots are moving from the science and manufacturing sectors and becoming ubiquitous in the retail and service environments (Barnett et al., 2014; Iocchi, Chen, & Hsu, 2016). A growing movement aims to develop robots that provide more than service automation but act as sales staff, product advisors, shopping assistants for the general public (Barnett et al., 2014). These robots are designed to create compelling high-tech shopping experiences and personalized customer service to trigger engagement in retail stores (Li, Rau, & Li, 2010; Lin et al., 2016). Already, Lowe's, an omni-channel home improvement company, has brought autonomous robots dubbed "the LoweBot" into their stores. The LoweBot understands and speaks multiple languages and guides customers to find products on the store's shelves. The LoweBot serves as a translator and instantly provides up-to-date stock information to customers. It also functions as a real-time inventory tracking system (Lowe's Companies, 2016). This shift to using advanced robotic technologies in retail presents far-reaching benefits and challenges to the consumer researcher, the engineer, the psychologist, the robotician, the entrepreneur, and the public policy-maker (Lin et al., 2016).

The role of robots is continuously evolving toward becoming "partners" in various social environments including business, homes, hospitals, social services environments, and educational settings (Barnett et al., 2014; Christensen, Huttenrauch, & Severinson-Eklundh, 2000; Lin, Yueh, Wu, & Fu, 2014; Severinson-Eklundh, Green, & Hüttenrauch, 2003). This study aims to help fill the need to better understand the rapid advances in robotics and artificial intelligence (AI), particularly in the service sectors. This researcher uses the term "retail service robot" (RSR) to refer to a robot with AI that uses big-data knowledge from consumer behavior databases to provide useful and smart in-store customer service (Kiesler & Hinds, 2004). The current study identifies influential factors that affect the outcome of interaction to support and improve customers' interactions with RSRs. The study focuses on a robot's characteristics such as advanced intelligence, functionality, social capability, appearance, and consumers' anxiety toward robots. Most importantly, it provides a unified frame that explained what specific robot attributes facilitate or inhibit the acceptance of RSRs. Further, this study explains the basis for why customers might want to interact with a robot and their intention to accept RSRs. This study uses Human-Robot Interaction (HRI) as the basis for these attitudinal factors (Beer, Prakash, Mitzner, & Rogers, 2011). The researcher proposes that HRI is central to the user's perception and a key factor in their acceptance of RSRs (Barnett, Keeling, & Gruber, 2015; Beer et al., 2011). Successful HRI might also enhance customers' evaluation of the anticipated service quality from future shopping experiences (Goodrich & Schultz, 2007).

However, the public is so far largely unacquainted with robots in the retail context. Due to a lack of understanding about robots, some challenges to communication might exist because people fear robots or AI and feel anxious about any negative impact on their lives such as infringement of privacy and mechanical malfunction that lead to accidents in a harmful way (Young, Hawkins, Sharlin, & Igarashi, 2009). Furthermore, consumers or users can react quite differently to RSRs than they do to other technologies because robots are capable of complex interpersonal communication and emotional interaction (Kim, Kwak, & Kim, 2013). This interaction raises the potentially difficult issue of users' acceptance of businesses that want to integrate these new technologies into their operations (Kim et al., 2013).

Because of the increasing exposure of robots to the public through the media, human expectations for HRIs already wildly exceed merely fulfilling the basic functions of machines. This anticipation and the phenomenon of HRI raise such questions as how robots should behave and what characteristics they should have. To draw out these psychological and social aspects of RSRs, this researcher conducts personal interviews and a focus group to explore an emerging meaning of robot interactions in depth and to provide a more holistic view of what defines the user's acceptance of RSRs in retail and service environments. The researcher then proposes that a user's initiation of a positive HRI requires a complex deliberation of three attributes of a robot that are geared to facilitate a successful HRI: its degree of functionality, social capability, and appearance (Beer et al., 2011). The functionality consists of perceptions of usefulness and intellectual intelligence, the social capabilities comprise a perception of social intelligence and social expressivity, and the robot's appearance entails humanlikeness and attractiveness. However, the effect of these facilitators can be inhibited by users' preconceived anxiety toward robots (Beer et al., 2011). The researcher proposes that this negative emotion toward robots can trigger communication avoidance with RSRs (Nomura, Kanda, Suzuki, & Kato, 2008).

Using the Computers Are Social Actors (CASA) theory (Nass, Steuer, & Tauber, 1994) and the domestication theory (Haddon, 2006; Hirsch & Silverstone, 1992) as underlying theoretical frameworks, this study asks how potential users of RSRs form their attitudes toward HRI and how their attitudes influence their anticipation of service quality and the extent of their acceptance as measured by their intentions to use RSRs. The researcher generates three video stimuli of RSRs with each stimulus in one of the three consumer product/service categories: fashion (apparel), technology (mobile phone), and food service (restaurant). The researcher then builds a model of consumer acceptance of RSRs that explains how the attitudes toward HRI are molded by the facilitators and the anxiety toward robots, ultimately increasing the anticipation of service quality and the intention to use RSRs. Further, the model rationalizes how the anticipated service quality might impact on the acceptance.

Statement of the Problem

Despite the growing advances in intelligent robotics, the novelty of robots presents some challenges to creating positive attitudes in consumers toward their use because of distrust and anxiety toward robots (Goodrich & Schultz, 2007; Mahfouz, Philaretou, & Theocharous, 2008). Imagine a consumer receiving first-class service from a robot that can deliver fully-automated shopping experiences. And the robot can perform this service with intellectual abilities similar to a human, such as the ability to learn, reason, use language, have interpersonal conversations and formulate creative ideas. However, despite all of these capabilities and benefits of using it, the consumer does not feel comfortable with the interaction (Kirwan, 2016). Most of the current literature focuses on scientific or technical problems in robotics and discusses HRI issues from a strictly mechanical and computational perspective (Kiesler & Hinds, 2004; Lakshantha & Egerton, 2016; Strait, Vujovic, Floerke, Scheutz, & Urry, 2015). In particular, literature is inadequate in explaining psychological disputes of what makes consumers be interested in interacting with robots that fill sales or service roles. Further, consumers' perspectives of how they perceive a RSR is currently poorly understood both in terms of its social capability and appearance (Christensen et al., 2000; Lakshantha & Egerton, 2016).

From the early explorations of interaction with robots, HRI studies have found that people seem to perceive robots to often be more humanlike than most other computer technologies (Christensen et al., 2000; Friedman, Kahn Jr, & Hagman, 2003; Lee, Šabanović, &

Stolterman, 2016; Leite, Martinho, & Paiva, 2013). Even for the simplest form of an autonomous robot, such as the robot vacuum cleaner known as the Roomba, people seem to ascribe human traits to it and anthropomorphize it (Kiesler & Hinds, 2004). As a result, the extent of the acceptance of RSRs appears to differ from other computer-related technologies because humanlike robots are not perceived as machines but as other living beings thought to possess consciousness (de Graaf, Allouch, & Klamer, 2015). This phenomenon is called "anthropomorphism," the "assignment of human traits and characteristics" to nonhuman things. In this case, people seem to perceive that autonomous robots possess human abilities (i.e., the ability to think and perform a task by themselves), and they see robots as more mindful than most other computer technologies (Nass & Moon, 2000, p. 82). Users can perceive robots as social partners because they can be kind, polite, helpful, aggressive, humorous, and even display gender-type characteristics (de Graaf et al., 2015; Tay, Jung, & Park, 2014).

Nonetheless, there is scarce research on the development of a theoretical model that attempts to explain the relationship between the degree of social capability of RSRs and how people form their attitudes on interacting with or avoiding robots in retail and service settings. Moreover, the role of robots is continuously evolving toward becoming "partners" in various social environments such as business, homes, hospitals, social services environments, and educational settings (Barnett et al., 2014; Christensen et al., 2000; Lin et al., 2014; Severinson-Eklundh et al., 2003). While the general models for the acceptance of technologies such as the TAM model (Davis, 1989), the Unified Theory of Acceptance and Use of Technology model (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), and the Chain model (Goodhue & Thompson, 1995) contribute to understanding users' acceptance of computer-related technologies, they do not encompass the characteristics of today's innovations concerning robots, such as robot intelligence, social capability, and humanlike appearance (Beer et al., 2011). Further, they lack consideration of social variables and an understanding of human-to-machine “interaction” and instead emphasize the study of external variables of perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003; Young et al., 2009). Furthermore, due to the advancement of AI and anthropomorphic design, robots become cognitively and aesthetically resembling humans. They are highly automated, perceptive, communicative, and responsive to the environment, which is different from other forms of computer or internet technologies (Chiang & Chang, 2013; Lee et al., 2016). Thus, a new theoretical model is needed to explain consumers’ attitudes toward HRI and the acceptance of RSRs. Therefore, this study aims to extend the field of inquiry to the psychological and social impact of RSRs.

Purpose of the Study

The primary objective of this study is to build a theoretical model on the acceptance of RSRs that explains how consumers’ attitudes toward HRI are influenced by facilitators and enhance both the anticipated service quality and the acceptance of RSRs. The researcher uses three types of retail and service settings to determine whether and how perceptions of facilitators, such as functionality (i.e., usefulness and intellectual intelligence), social capability (i.e., social intelligence and social expressivity), and appearance (i.e., humanlikeness and attractiveness), form favorable attitudes toward interacting with a robot. The second objective is to provide empirical support that the relationship between these facilitators and attitudes toward HRI is moderated by the pre-existing anxiety toward robots.

The third objective is to investigate how consumers' attitudes toward HRI influence their evaluation of the service quality and the acceptance of RSRs and whether the anticipated service quality has positive impacts on the acceptance.

To accomplish these objectives, in the early stage of the study the researcher conducts personal interviews and a focus group. Based on the literature review and this qualitative information, the researcher develops three video clips about robots for use in a survey. These clips cover three product or service categories: fashion (apparel), technology products (mobile phone), and food services (restaurant). To address the three main objectives of this study, the researcher focuses on three open questions:

1. What attributes of RSRs facilitate the formation of favorable attitudes toward HRI?
2. How does a user's preconditioned anxiety toward robots inhibit the formation of positive attitudes toward HRI?
3. How do a user's attitudes toward HRI affect their evaluation of the service quality and the intention to use a RSR?

Drawing upon the CASA theory (Nass et al., 1994) and the domestication theory (Haddon, 2006; Hirsch & Silverstone, 1992), this study examines how social capability and the physical attributes of a robot, in addition to its functionalities, influence consumers' attitudes toward interacting with or avoiding robots. Furthermore, this study investigates how consumers' pre-existing anxiety toward robots inhibits their rapport with RSRs. Based on the literature review, personal interviews, an interview with a focus group, and consumers' responses to video clip stimuli about robots, this study aims to investigate:

1. The facilitating role of consumers' perceptions of RSRs in forming positive attitudes toward HRI such as functionality of usefulness and intellectual intelligence, social capabilities of social intelligence and social expressivity, and appearance of humanlikeness and attractiveness;

2. The inhibiting role of anxiety toward robots in the relationship between the six facilitators of consumers' perceptions of RSRs and their attitudes toward HRI;

3. The relationship between consumers' attitudes toward HRI and the extent of the anticipation of service quality and acceptance as measured by the behavioral intention to use robots.

Definitions of Terms

The conceptual definitions of the constructs in this study are presented in Tables 1.

Table 1. The conceptual definitions of the constructs.

Construct	Definition	Source
Retail Service Robot	An in-store customer service robot with AI to help customers in navigating a store, finding products and information, and completing purchase transactions.	Barnett et al. (2014); Christensen et al. (2000)
Usefulness	A consumer’s perception of a RSR’s utility such as practicality, efficiency, and effective task performance (e.g., improving shopping effectiveness, helping to complete a purchase transaction, providing personalized product information, and helping a product search).	Davis (1989)
Intellectual intelligence	A consumer’s perception of the intellectual ability of a RSR, such as displaying knowledgeability, competency, sensibility, and intelligence.	Bartneck, Croft, and Kulic (2008)
Social intelligence	A consumer’s perception of a RSR’s social aptitude such as the ability to have an appropriate conversation, to listen attentively, to be nice, and to be polite.	De Ruyter, Saini, Markopoulos, and Van Breemen (2005)
Social expressivity	A consumer’s perception of a RSR’s expressive characteristics in an interactive communication such as being socially expressive and communicative, and sending affective signals while talking to a customer.	De Ruyter et al. (2005)
Humanlikeness	A consumer’s perception of a RSR’s physical manifestation of a human or closeness to human characteristics in appearance and movement.	Bartneck et al. (2008)
Attractiveness	A consumer’s perception of a RSR as being visually attractive or good looking.	Srinivasan, Anderson, and Ponnavolu (2002)
Anxiety toward robots	A consumer’s pre-existing feeling of anxiety about a RSR in terms of communicating with a robot or disclosing information to a robot. The anxiety toward robots might have built through prior robot experience or media exposure.	Nomura, Suzuki, Kanda, and Kato (2006)

Table 1. The conceptual definitions of the constructs (continued).

Construct	Definition	Source
Attitudes toward HRI	Consumers' positive attitudes toward interaction with RSRs in a store environment.	Nomura and Kanda (2003) and Nomura et al. (2008)
Anticipated service quality	Overall consumer evaluation and expectation of service delivery in a store environment that employs RSRs as sales staff, service providers, and shopping assistants.	Lee and Lin (2005)
RSR acceptance	The behavioral intention or inclination to use a RSR in the future when it is available in a store.	Davis (1989) and Davis, Bagozzi, and Warshaw (1989)

CHAPTER II
LITERATURE REVIEW

This chapter consists of four sections that provide the theoretical and conceptual groundwork for this study. The first section presents a literature review of RSRs. It also presents a theoretical background that explains how humans perceive robots differently from other computer technologies and why an acceptance model needs to be built. The second section presents an overview of the literature on the factors that might either facilitate or inhibit HRI. The third section covers the components of HRI and the potential users' expectations on service quality. It also discusses the consumers' behavioral intention to accept RSRs. The fourth section presents the hypotheses and the acceptance model that illustrates the mechanism of how consumers interact with RSRs in a store.

Retail Service Robots (RSRs)

Retail service robots (RSRs) are intelligent machines capable of assisting customers with a high degree of autonomy or without any human control in the retail and service sectors (Kiesler & Hinds, 2004). Reflecting descriptions of service robots from Barnett et al. (2014) and Christensen et al. (2000), the researcher defines RSR as an in-store customer service robot with AI to help customers in navigating a store, finding products and information, and completing purchase transactions. Although these robots have not been widely commercialized yet, RSRs are designed to create a comfortable shopping experience, provide accurate product information and recommendations, entertain customers, collaborate with in-store human staff, update real-time inventory information, and engage customers in friendly interactions (Barnett et al., 2014; Christensen et al., 2000). RSRs can also assist with customer service requests: robots can carry bags, give directions, provide transportation, help people get up and down stairs, and enable people with disabilities to be independent shoppers (Kiesler & Hinds, 2004). These robots are capable of expressing emotions and performing social activities such as providing advice and discussion (Tay, Low, Ko, & Park, 2016).

Businesses have developed and commercially adopted various types of robots for use in a variety of areas such as sales, service, household use, warehouse automation, and entertainment (Park & Del Pobil, 2013). For example, in 2014 SoftBank Robotics introduced a humanlike robot called “Pepper” in Japan. To date, Peppers have been actively used as sales staff for welcoming, informing, and servicing consumers in more than 140 SoftBank Mobile stores in Japan (SoftBank Robotics, 2016). The Pepper robot was developed as an emotional and socially interactive robot that can recognize a user’s facial expression, body movement, and verbal expression and respond to the customer’s needs and inquiries precisely (SoftBank Robotics, 2016). After an extensive video selection process, this study chose Pepper as the focus of the video stimuli because it is suitable for our aim of studying HRI (Figure 1).

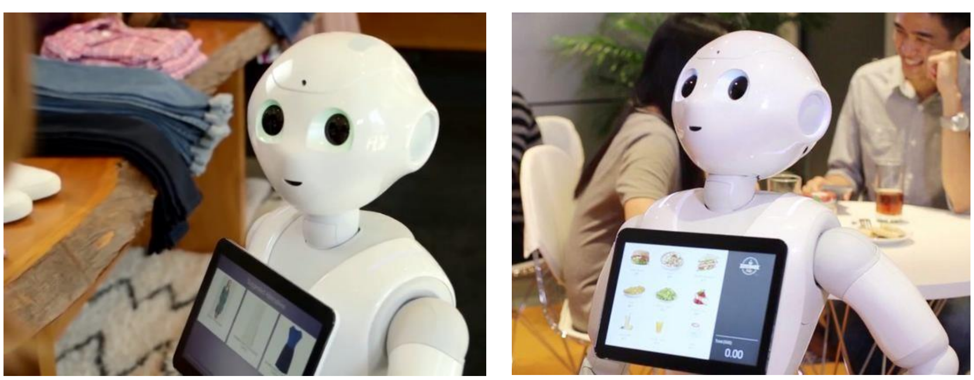


Figure 1. The humanoid robot “Pepper” manufactured by Softbank Robotics.

Human-Robot Interaction

The robotic engineering discipline originally outlined Human-Robot Interaction (HRI) as "a field of study dedicated to understanding, designing, and evaluating robotic systems for use by or with humans" (Goodrich & Schultz, 2007, p. 204). The study of HRI gauges the psychological reactions of robot users to describe their evaluations of how humans collaborate and interact and use those robot technologies cognitively and emotionally (Young et al., 2009). While most of the studies on intelligent robots predominantly are dedicated to the technical development of robots, the research on users' attitudes toward interaction with robots is comparatively unexplored (Bartneck, Suzuki, Kanda, & Nomura, 2007; Park & Del Pobil, 2013; Stafford, MacDonald, Jayawardena, Wegner, & Broadbent, 2014).

Consumers' attitudes toward a technology can be formulated by both affective (e.g., comfort, pleasure, enjoyment) and cognitive (e.g., knowledge exchange, product learning, and information research) components (Batra & Ahtola, 1991; Kempf, 1999). Hence, the researcher delineates the attitudes toward HRI as consumers' positive viewpoints toward interaction with RSRs emotionally and intellectually (Bartneck et al., 2007; Nomura & Kanda, 2003; Nomura et al., 2008). This study uses the construct of attitudes toward HRI that includes both affective and cognitive evaluations such as "I would feel relaxed talking with the retail service robots," "I would enjoy interacting with retail service robots," and "talking to the retail service robot would help me learn about a product."

The literature on HRI finds that the interaction with a non-human entity is similar to the communication between humans (Beer et al., 2011; Kim et al., 2013). Further, the attitudes toward HRI might be strongly dependent on the approaches to the communication (Steinfeld et al., 2006). This capacity of communication can be influenced by how consumers perceive a robot in terms of its characteristics and appearance (Barnett, Keeling, et al., 2015; Beer et al., 2011). Therefore, positive perceptions should facilitate the magnitude of favorable attitudes toward RSRs while negative perceptions should diminish consumers’ motivation to interact with them (Beer et al., 2011; Dautenhahn, 2007; De Ruyter et al., 2005).

Theoretical Framework

This research aims to explore consumers’ perceptions of RSRs and their attitudes toward HRI. It also investigates how their pre-existing anxiety toward robots might inhibit the relationship between consumers’ perceptions and HRI. Furthermore, the researcher examines how consumers’ favorable attitudes toward HRI might influence their anticipation of service quality that eventually affects their level of acceptance—the intention to use RSRs in retail environments.

The research on Technology Acceptance Models (TAMs) indicates that the perception of functionality, such as usefulness and ease of use, has considerable effects on users’ acceptance, attitudes, beliefs, and behaviors toward technologies (Davis, 1989; Venkatesh et al., 2003). Thus, a utilitarian factor of usefulness in robot technologies might play a crucial role in the acceptance of an RSR, just as they do in the adoption of other computer technologies (de Graaf et al., 2015). However, new AI applications in robot technologies have enabled humanlike communication between robots and users especially in commercial sales and service (Krämer, von der Pütten, & Eimler, 2012). According to the exploratory study by de Graaf et al. (2015), when users ascribe humanlike and social characteristics to a robot, they are more likely to interact with it; thus, the perceived usefulness of a robot tends to increase. The consumer’s acceptance of these intelligent robots requires acceptance of several technological innovations such as AI, speech recognition, image processing, and wireless technologies (Oyedele, Soonkwan, & Minor, 2007). Nonetheless, many TAM related models do not adequately focus on the social and aesthetic aspects of technologies, such as the perceptual and emotional factors surrounding “interaction,” “collaboration,” and “social exchange.” This lack of attention is particularly clear in the study of service technologies (Davis, 1989; de Graaf et al., 2015; Venkatesh et al., 2003). Thus, a RSR acceptance model needs to be built that takes these social and appearance factors into account in additional to functional factors.

Two theoretical backgrounds support the formation of consumers’ acceptance model. First, the CASA theory provides a theoretical framework for how consumers form their attitudes toward HRI based on social capability and robot appearance. Second, the domestication theory (Haddon, 2006; Hirsch & Silverstone, 1992) explains both the utilitarian and social aspects of the technologies and argues for the importance of social acceptance of new technologies as a part of everyday life (Haddon, 2006; Hynes & Richardson, 2009).

Computers Are Social Actors Theory

The CASA theory originated from Nass et al. (1994). Their experimental study of HRI explains that the relationship between computers and users is fundamentally a social one. The results of their five laboratory experiments indicate that computer users subconsciously apply social rules to their interactions with their computers in much the same way as they do in human-to-human interactions. Although users are aware that a computer is not human, they still intuitively treat it like a human. For instance, people tend to apply gender stereotyping to computers and robots. Users are likely to ascribe negative stereotypes to female-presenting robots while they assume that male-presenting robots are more proficient than the female ones (Brahnam & De Angeli, 2012). Such social responses to computers also include users' perception of social characteristics and assignment of human personality to computers. For example, when the computer uses language during the interaction "you should definitely do this," then users tend to describe its characteristics as "assertive" or "dominant." When it uses more ambiguous language "perhaps you should do this," then users are likely to assign its attributes as "submissive" (Nass & Moon, 2000, p. 91).

Based on the premise of the CASA theory, the researcher assumes that when an RSR provides sufficient basis to cue "social capability" and "humanness," these cues will encourage social and emotional responses. Therefore, the interaction between a robot and an individual will be more pleasant (Nass et al., 1994). The researcher applies the CASA paradigm to HRI by investigating whether consumers exhibit the same patterns of social responses toward RSRs that they display in human-to-human interactions.

Domestication Theory

The domestication theory provides a broader overview of technology acceptance and resistance by explaining the processes by which technologies are accepted, used, or rejected by people and how innovations are integrated into users' daily practices in a domestic environment (Haddon, 2006; Hirsch & Silverstone, 1992). The domestication theory was developed to understand the adoption of new media or communication technologies for household use by focusing on interpersonal and social relationships with technologies (Hirsch & Silverstone, 1992). Later theoretical models of domestication have been expanded to include other technologies consumption patterns (e.g., users' behavior of internet and mobile phones) to explain how innovations are adopted and shaped sociologically (Haddon, 2006; Iocchi et al., 2016; Rijsdijk & Hultink, 2003; Young et al., 2009). For example, de Graaf, Allouch, and van Dijk (2016) indicate that users of socially interactive robots evaluate the robots based on their previous experiences with robotic technologies prior to interaction. However, once the users start interacting with the robots, they form their attitudes heavily based on utilitarian, social, and hedonic factors such as usefulness, social presence, and enjoyment which eventually encourage users' acceptance of robots in long-term. Moreover, when a robot is capable of verbal communication, users perceive not only its functionality of intellectual intelligence but also form their expectation of sociability to robots. Through perceiving social cues, users tend to personify the robot and social capability of robots increases their emotional bonds with it (de Graaf, 2016).

Focusing on the user's perspective on technological innovation, the domestication theory proposes that consumers' technology acceptance is a complex process of individual choices that interweave the functional, social, and aesthetic attributes of technologies (de Graaf et al., 2015; Silverstone & Haddon, 1996). Thus, the researcher takes this domestication approach to the acceptance of RSRs that considers both functional and social aspects of robots that are important parts of consumers' everyday use of the technologies. To start any type of successful interaction, robots should be socially and aesthetically acceptable to initiate active interaction with humans (de Graaf et al., 2015; Rijsdijk & Hultink, 2003; Young et al., 2009).

The domestication approach that describes the integration of technologies into social settings is traditionally studied by qualitative or ethnographic research methods (e.g., face-to-face interviews, focus group interviews, and ethnography). While this study does not attempt to find qualitative results, the researcher examines consumers' general opinions about RSRs in a retail setting by conducting a focus group interview and face-to-face interviews to explore the emerging meaning of robot technologies.

Facilitators of Human-Robot Interaction

Based on the CASA and the domestication theories, a RSR is presumably treated as a social actor that communicates with humans socially. According to CASA, people prefer communicating with a robot whose physical appearance is more like a human. The greater the humanlikeness of a robot, the more important the face-to-face interaction with it (Li, 2015). Thus, in addition to functionalities and social abilities, nonverbal communication (e.g., facial expressions and body movement) also becomes an important aspect of a positive HRI as a means of social exchange (Beer et al., 2011; Littlewort et al., 2003). Through the literature review, the researcher classifies the facilitating factors into three categories of HRI that provide crucial cues to consumers' intentions and influence their views of the robot's propensities and postulations: functionality, social capability, and appearance (Beer et al., 2011; Goodrich & Schultz, 2007). When consumers perceive these functionalities of a product or service, they are more likely to form positive attitudes toward the product (Ko, Cho, & Roberts, 2005). The research also shows that the social capability of technologies is crucial to consumers' attitudes toward interaction with the technologies (Chee, Taezoon, Xu, Ng, & Tan, 2012; Steinfeld et al., 2006). Further, the physical appearance of robots is known to be a major external factor that determines the extent of HRI (Beer et al., 2011) (see Table 2).

Through a focus group and personal interviews, the researcher reconfirms the pool of potential influencers of HRI: usefulness, intellectual intelligence, social intelligence, social expressivity, humanlikeness, and attractiveness and the inhibiting factor of anxiety toward

Table 2. Main categories of facilitators of HRI.

Key categories	Definition	Source
Functionality	A consumer' view of the worth of RSRs as to whether they are helpful in improving the efficiency of shopping, advance their product knowledge, provide personalized product information, and help to complete purchase transactions: • Usefulness and intellectual intelligence	Davis (1989); Bartneck et al. (2008); Beer et al. (2011)
Social capability	A consumer's view of a RSR' ability to communicate with humans and its characteristics to be socially acceptable. This includes the customers' perception of robot's sociability such as having an appropriate conversation and possessing socially expressive characteristics: • Social intelligence and social expressivity	De Ruyter et al. (2005); Beer et al. (2011); Kim et al. (2013)
Appearance	A consumer's perception of a RSR' physical attributes such as closeness to human characteristics in appearance and movement or the aesthetic attraction: • Humanlikeness and attractiveness	Bartneck et al. (2008); Srinivasan et al. (2002)

robots. The robot's functionality consists of two subcategories of usefulness and intellectual intelligence—the abilities to provide knowledgeable advice and information (Barnett, Keeling, et al., 2015; Beer et al., 2011); the robot's social capability comprises two sub-factors of social intelligence and social expressivity—sociability and communicability (Beer et al., 2011; Dautenhahn, 2007; De Ruyter et al., 2005); and the robot's appearance comprises the humanlikeness and attractiveness of a service robot (Goetz, Kiesler, & Powers, 2003). Further, the researcher proposes that a customer's preconditioned anxiety toward RSRs might moderate the effect of the facilitating factors of a RSR on the attitudes toward HRI. In the following section, the researcher provides an overview of the factors in play in this research and proposes the hypotheses based on their interrelationships.

Functionality

Consumers often view the worth of a technology product or service as whether it improves the efficiency of some tasks, advances their knowledge or skills, provides a new means of communication, increases the effectiveness of the product, or simply provides a good experience (Davis, 1989; Ko et al., 2005). Uncertainty about the functional benefits of a product, on the other hand, becomes a risk toward the usage of it, consequently lessening consumers' expectation of service quality and the intention to use the product (Erdem & Swait, 1998). Thus, the functionality of a new technology is one of the fundamental aspects that influence consumers' evaluation of product and service performance. In this study, the functionality of RSRs has two subcategories: usefulness and intellectual intelligence (Barnett, Keeling, et al., 2015; Beer et al., 2011).

Usefulness

In the domain of information technologies, perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). This user's perception of an RSR's performance, such as practicality, efficiency, and effective task operation, is formed based on the user's needs (Dahl, Chattopadhyay, & Gorn, 1999; Davis, 1989). In this study, usefulness is defined as the consumers' perception of the perceived utility of a RSR based on consumers' needs for shopping, such as improving shopping effectiveness, helping to complete purchase transaction, providing personalized product information, and helping a product search (Chang & Wang, 2008; Davis, 1989). The construct of usefulness is operationalized by describing a RSR's functional values such as “using the RSR would save me time,” “it would be easy to shop with the RSR,” “using the RSR would improve my shopping ability,” and “using the RSR would enhance my effectiveness during shopping.”

The literature shows that a close relationship exists between the usefulness of technologies and a user’s favorable attitudes (Davis, 1985, 1989). This literature well establishes usefulness as a strong predictor of positive attitudes particularly in the context of internet use, computer-mediated environment, and technology adoption behavior (Antón, Camarero, & Rodríguez, 2013; Chau, 1996; Davis, 1989). Fred Davis (1989) emphasizes the importance of this powerful variable in technology acceptance in the TAM. Since Davis, the literature has frequently used perceived usefulness to predict users’ attitudes, experience, and acceptance of new technologies (i.e., the behavioral intention to use the technologies) (Antón et al., 2013; Morgan-Thomas & Veloutsou, 2013; Park & Kim, 2014). Thus, the researcher assumes that the perceived usefulness of RSRs might also be a dominant cause of interaction between humans and robots. Hence, as consumers assign a greater level of usefulness to a RSR, they are more likely to form positive attitudes about interacting with it (Chau, 1996). Based on the above, the researcher hypothesizes H1a.

H1a: A RSR’s perceived functionality of *usefulness* will positively influence consumers’ attitudes toward HRI.

Intellectual intelligence

AI enables consumers to gain knowledge about products and information and changes the way that they interact with the technologies (Davis, 1989; Kim et al., 2013; Venkatesh et al., 2003). Specially, because RSRs use AI, the robot's intellectual intelligence such as being knowledgeable, intelligent, and competent in providing advice and a personalized recommendation should be an important characteristic that determines users' trust (Proia, Simshaw, & Hauser, 2015). Intellectual intelligence, in this study, is defined as users' perception of a RSR's intellectual ability or its capability of providing information that helps users learn about products and guides to make an informed purchase choice (Bartneck et al., 2008). The construct of intellectual intelligence is operationalized by describing a RSR's cognitive and intellectual ability such as "the retail service robot appears to be competent," and "the retail service robot seems to be knowledgeable."

Robots' behaviors and responses to humans are based on AI (Barnett, Keeling, et al., 2015; Beer et al., 2011). This perceived intelligence is a standard measure of a robot's HRI capability (Bartneck et al., 2008). For example, if a consumer's body measurement had been scanned previously, he or she could rely on a robot with AI to pick the size garments that will most likely fit his or her body size. If that is the case, the consumer does not have to try all sizes on, which saves time and effort when shopping for clothes. Further, if the robot sales associate appears to provide accurate information such as available sizes, colors, and stock inventories in the store, the consumer will be more likely to trust the RSR (Madsen & Gregor, 2000). Moreover, when a RSR appears to possess the capability of reasoning, solving problems, and learning quickly, consumers might perceive it intellectually intelligent. This information and knowledge aspects of a RSR would be another fundamental functionality that helps consumers make their shopping decisions more easily (Gottfredson, 1997). Thus, as consumers assign a greater level of intellectual intelligence to a RSR, they are more likely to form positive attitudes about interacting with it. Therefore, the researcher hypothesizes H1b.

H1b: A RSR's perceived functionality of *intellectual intelligence* will positively influence consumers' attitudes toward HRI.

Social Capability

Based on the CASA theory, consumers might perceive robots as social actors and the research should consider their social presence a factor that influences the acceptance of robot technologies (Nass & Moon, 2000; Nass et al., 1994). Further, the research frequently mentions the social dimension of a technology as a powerful tool for engaging users in the interaction between humans and robots (Chee et al., 2012; Steinfeld et al., 2006). Nonetheless, the theoretical framework for acceptance that incorporates the social capability of robots has not been discussed much in the past. Thus, this study includes the social effects of communication with RSRs in the research model to determine whether the social aspects of robots increase the positive attitudes toward interaction. The researcher proposes that the degree of success in human-robot collaboration depends on the extent to which a robot is socially communicable, interpersonal, and approachable. This ability relies on two sub-factors in a RSR's social capability: social intelligence and social expressivity (Beer et al., 2011; Kim et al., 2013).

Social intelligence

This study defines social intelligence as the perceived social aptitude of a RSR such as the ability to have an appropriate conversation, to listen attentively, to be nice, and to be polite (De Ruyter et al., 2005). In human-to-human interaction, a person who possesses socially intelligent characteristics tends to be more liked by others and to be perceived as pleasant to speak with (Sternberg & Smith, 1985). Social intelligence, which comprises self-awareness and social skill, is a cognitive ability to effectively manage intricate social relationships and environments. The origin of social intelligence is from Thorndike (1920), an American psychologist in modern educational psychology. He defines social intelligence as “the ability to understand and manage men and women, boys and girls, and to act wisely in human relations” (Thorndike, 1920, p. 228). Put another way, social intelligence is the ability to get along with people and having knowledge of social matters (Gardner, 2011; Mayer & Salovey, 1997). These social attributes also include characteristics that make a person “trustworthy,” “competent,” and “friendly.” These characteristics can also be applied to designing a humanlike robot and a robotic interface that stimulate social interaction with users (De Ruyter et al., 2005). This study operationalizes the construct of social intelligence through a RSR’s cognitive and intellectual ability such as “the retail service robot appears to listen attentively,” “the retail service robot appears to say appropriate things,” “the retail service robot seems to remember the detailed information about the customer's questions,” and “the retail service robot appears to be polite.”

Based on the CASA theory of Nass et al. (1994), humans unconsciously apply the social heuristics of human-to-human interaction when interacting with computers and tend to assign human characteristics to computers and treat them as humans. In recent commercial applications of robots, RSRs have emerged as social partners rather than a mechanical tool such as a hotel or hospital service staff, shopping assistants, and sales event staff (Breazeal, 2004; Lowe's Companies, 2016). With the evolution of AI and robotics, robots' social skills and interactive ability have become necessary requirements in service application fields (Barnett, Foos, et al., 2015; Dautenhahn, 2007; de Graaf et al., 2015). Nonetheless, the research on HRI has challenges in determining the effect of social intelligence and the nature of social behavior in robots (Barnett, Foos, et al., 2015; Dautenhahn, 2007). This study addresses these challenges. Similar to human-to-human interaction, when users perceive a RSR as socially intelligent, this perception might lead to positive HRI attitudes as they feel comfortable, enjoyable, and receptive to interacting with robots (Dautenhahn, 2007; De Ruyter et al., 2005; Kim et al., 2013; Nass & Moon, 2000). The researcher thus posits the following hypothesis H1c.

> **H1c:** A RSR's perceived social capability of *social intelligence* will positively influence consumers' attitudes toward HRI.

Social expressivity

Social expressivity is defined as a user's perception of expressive characteristics of an RSR in an interactive communication (De Ruyter et al., 2005). Through voice and body, the expressivity of a RSR plays a role in conveying the meaning of the information and helps in maintaining the users' attention and engagement in the interaction (Pelachaud, Gelin, Martin, & Le, 2010). The recent research shows that expressive robots tend to stimulate a willingness to disclose more personal information that results in companionship (Martelaro, Nneji, Ju, &

Hinds, 2016). Users who interact with an expressive robot sometimes feel that the robot appears to care about them and seems to be reliable. In contrast, users who interact with a robot with low expressivity often feel that the interaction is awkward. Consequently, they do not trust or feel companionship with the robot (Martelaro et al., 2016).

In line with this point of view, consumers' perception of social capabilities such as verbal expressiveness and nonverbal social signals can affect their viewpoint about interaction and acceptance (Beer et al., 2011). In particular, verbal expressivity is one of the most important social cues that makes a robot seem trustworthy and believable (Beer et al., 2011). This study thus operationalizes the construct of social expressivity as a RSR's verbal communicability and its ability to comprehend and reason such as "the retail service robot appears to be expressive," and "the retail service robot appears to display an appropriate expression to the customer's confusion." Based on above, the researcher supposes that a RSR's expressive attribute can effectively engage consumers in interactive communication and proposes that attitudes toward HRI can be dependent on the expressive characteristics of the robot. The researcher thus hypothesizes H1d.

> **H1d:** A RSR's perceived social capability of *social expressivity* will positively influence consumers' attitudes toward HRI.

Appearance

Robots become more intelligent, socially interactive, and mimic humans more closely based on the premise that a humanoid robot produces the best communication experience for people (Hinds, Roberts, & Jones, 2004). Consumers form their impressions about the medium of their communication from the outer appearance quickly by analyzing the physical attractiveness, familiarity, and the nonverbal actions of robots (Beer et al., 2011). While robots are programmed to satisfy consumers' physical, psychological, or social needs (Oyedele et al., 2007), little concrete data from psychological models exist that support the influence of robots' physical appearance on consumers' HRI attitudes (Beer et al., 2011; Li et al., 2010; Oyedele et al., 2007). Consumers' expectations on how the robot should look like vary (Beer et al., 2011; Libin & Libin, 2004). In this study, the researcher finds the overall effect of the physical impression on attitudes toward HRI depends on the humanlikeness and attractiveness of the RSR.

Humanlikeness

Humanlikeness is defined as a user's perception of physical characteristics in appearance and movement (Bartneck, Kulić, Croft, & Zoghbi, 2009). With the first impression of appearance, people tend to form a set of expectations of a robot's abilities even before any interaction begins (Li et al., 2010). As discussed in the CASA and the domestication theories, people expect robots to behave and interact in much the same way as humans (Goodrich & Schultz, 2007; Li et al., 2010). Thus, a robot's capacity to engage in meaningful social interaction naturally requires some degree of human qualities in appearance and behavior (Duffy, 2003).

However, the role of humanlike appearance in HRI is not so obvious. When the robot appears to have a close human resemblance but its movement and behaviors do not meet the user's expectation of humanness, then this disagreement negatively affects the social interaction between users and robots (Lockard, 2014). Further, the humanlike features of robots might potentially produce some fear if the user is unfamiliar with them (Dautenhahn, 1999, 2007). In an experiment study of HRI, Hinds et al. (2004) indicate that users perceive mechanical-looking robots as less polite and less socially interactive than the ones with a more humanlike appearance. Furthermore, users tend to evaluate robots with a greater level of humanlikeness as more functional and reliable than the mechanical-looking ones. To have the robots to complete the tasks, the users feel that they need to explain and provide more instructions to mechanical-looking robots than to humanlike robots. Walters, Syrdal, Dautenhahn, Te Boekhorst, and Koay (2008) also investigate users' perception of different robot appearances. Their results from video-based HRI trials show that people commonly prefer a more humanlike appearance of robots than mechanical-looking ones. However, Walters et al. (2008) suggest that consumers are generally pleased with the anthropomorphic appearance of robots at first sight, but they quickly get disappointed with the humanlike features after they actually interact with the robots. The preference of robot appearance could also vary among individuals and types of use (e.g., personal, domestic, and commercial use). Thus, more future work is needed to fully understand the users' perception and their preference for the robots' appearance. In this study, the construct of humanlikeness is operationalized by describing a RSR's humane appearance such as "the retail service robot looks natural," "the retail service robot appears humanlike," and "the retail service robot moves in a humanlike way."

Humanlikeness is applied to HRI based on a scientific understanding of how people interact with the different types or designs of robots. This design aspect, in turn, provides an important insight on how to engineer robots that interact effectively with users. This understanding leads to characteristics such as being more anthropomorphic (humanlike), animal-looking, organic, or mechanical to better service consumers' social, emotional, or cognitive needs in their shopping and service experiences (Breazeal, 2004). In terms of communication, designing human-shaped robots can provide an interface that is more natural than those offered by more mechanistic robots (Lee, Peng, Jin, & Yan, 2006). In this study, the researcher argues that humanlike appearance of a RSR will encourage interaction with consumers and help provide more friendly, comfortable, and intuitive interface. The humanlike design of RSRs might be an effective facilitator of HRI, convincing users to easily start communication. Thus, the researcher posits the following hypothesis H1e.

> **H1e:** A RSR's perceived appearance of *humanlikeness* will positively influence consumers' attitudes toward HRI.

Attractiveness

Attractiveness is defined as a user's perception of a RSR as being visually attractive or good looking (Srinivasan et al., 2002). The appearance of robots has continuously evolved since the early 1990s. The expectation of how robots should look today is quite different. While little research exists, it does find some associations between an attractive design, such as color and surface materials, and the perceived friendliness of robots (Chee et al., 2012). While consumers' needs for RSRs are evolving constantly, this study attempts to find a relationship between the attractiveness of robots and HRI that facilitates more effective communication with humans. This study operationalizes the construct of attractiveness as a RSR's appealing physical appearance such as "the retail service robot is attractive," "the retail service robot looks visually appealing," and "the retail service robot is good looking."

Niculescu, Van Dijk, Nijholt, and See (2011) assert that the user's evaluation of a robot is influenced by hedonic quality such as the robot's appearance appeal, task appeal, and content appeal. The appearance appeal indicates how the robot looks, behaves, and presents itself to others. The task appeal reflects how enjoyable the interaction with the robot is. The content appeal denotes how interesting and attractive the content is that the robot delivers. While both functional and hedonic qualities of robots interplay to create consumers' attitudes toward HRI, the increased level of a robot's attractiveness tends to generate greater enjoyment and a quality interaction between a social robot and users (Niculescu et al., 2011). Further, based on the CASA and the domestication theories, people treat a RSR as a social actor and make their judgments on its external features within a few seconds of meeting it just as in human-to-human interactions (Haddon, 2006; Hirsch & Silverstone, 1992; Nass et al., 1994). These instant appraisals can be primarily influenced by the visual attractiveness of RSRs (Walters et al., 2008). Thus, this study proposes that the physical attractiveness and likable appearance of RSRs may have a positive impact on consumers' attitudes toward HRI. The researcher thus hypothesizes H1f.

H1f: A RSR's perceived appearance of *attractiveness* will positively influence consumers' attitudes toward HRI.

An Inhibitor of Human-Robot Interaction

Although there is a growing need for the HRI research due to the growth of intelligent robot applications in business, it is not clear whether robots enhance consumers' retail experience or they are seen as threats to human employment (Kim et al., 2013). However, it is important to understand how consumers' preconception toward robots influences their perception of RSRs in all aspects (M Tsui, Desai, A Yanco, Cramer, & Kemper, 2011). Because of the unfamiliarity and fear of new technologies, consumers' pre-existing anxiety toward robots might negatively influence the relationship between perception and attitudes toward RSRs (M Tsui et al., 2011). Anxiety toward RSRs may come from negative experiences with robots in the past or negative media exposure (Bartneck et al., 2007; Steinfeld et al., 2006). The researcher anticipates that a broader acceptance of RSRs can occur when this anxiety is gradually lessened among consumers through the prevalence of robots in their daily lives—retail service robots; elderly care robots; home robots; or even domestic household robots that help with family chores such as robots cleaning swimming pools, vacuum-cleaning, floor-cleaning, and mowing lawns. In this study, the researcher investigates the effect of this pre-existing anxiety toward robots and hypothesizes on the moderating effect of anxiety toward RSRs on the relationship between the facilitators and the attitudes toward HRI.

Anxiety toward robots

Anxiety toward robots is defined as a consumer's pre-existing feeling of anxiety about a RSR in terms of communicating with a robot or disclosing information to a robot (Nomura et al., 2008). In other words, the anxiety toward robots is a pre-conditioned emotion that might inhibit forming attitudes on interactions with robots (Nomura, Kanda, Suzuki, & Kato, 2004). Such an anxiety toward robots among consumers might develop from prior experience or media exposure. This study operationalizes the construct of anxiety toward robots as consumers' anxious feeling and fear about robots such as "I would feel anxious about whether the retail service robot might talk about irrelevant things in the middle of a conversation," "I would feel anxious about how I should talk to the retail service robot," and "I fear that using a retail service robot would reduce the confidentiality of my personal information."

Today's robots with AI are equipped with advanced technologies such as real-time access to consumer information and inventory updates, and cutting-edge intelligence (Barnett et al., 2014; Christensen et al., 2000). However, many consumers are still unfamiliar with interactions with robots and express discomfort in letting robots do something for them. At the early stage of RSR entry into retail business fields, consumers were largely uncertain about the potential benefits of using RSRs. The risks can bring uncertainty about the robot's capability or accuracy of its performance, communication apprehensiveness, fear of using novel technologies, or questions about maintaining the confidentiality of personal information (e.g., credit card, financial, or medical information) (Meuter, Bitner, Ostrom, & Brown, 2005). Further, the field of educational psychology finds that such computer anxiety constrains users' ability to learn about computers and reduces their ability of technical problem solving (Nomura et al., 2004). Since RSRs are a new technology that heavily involves a computer system and AI, a comparable anxiety towards robots might exist and might inhibit individuals from communicating with robots. Hence, the researcher views that anxiety toward robots can be an inhibiting factor that influences the relationship between facilitators, such as functionality, social capability, and appearance of robots, and consumers' attitudes toward HRI.

Based on the above, the researcher proposes that customers' pre-existing anxiety toward robots might negatively influence the relationship between perception and attitudes toward HRI. Specifically, when consumers possess a low level of anxiety toward robots, the relationship between facilitators and attitudes toward HRI can be stronger than when consumers retain a high degree of anxiety toward robots. Conversely, when consumers possess a profound tendency for an anxious feeling toward robots, the opposite effect might occur that will negatively affect the formation of their attitudes toward HRI (Celik & Yesilyurt, 2013; Oyedele et al., 2007; Park & Del Pobil, 2013; Young et al., 2009). Thus, the researcher posits the following hypotheses:

Hypothesis 2: The effects of a RSR's facilitating factors on consumers' attitudes toward HRI is moderated by the level of their pre-existing anxiety toward robots.

H2a/b: The effects of the RSR's *usefulness* ***(H2a)*** and *intellectual intelligence* ***(H2b)*** on consumers' attitudes toward HRI are weaker when their anxiety about robots is higher.

H2c/d: The effects of the RSR's *social intelligence* ***(H2c)*** and *social expressiveness* ***(H2d)*** on consumers' attitudes toward HRI are weaker when their anxiety about robots is higher.

H2e/f: The effects of the RSR's *humanlikeness* ***(H2e)*** and *attractiveness* ***(H2f)*** on consumers' attitudes toward HRI are weaker when their anxiety about robots is higher.

Anticipated Service Quality

With the emergence of robots in retail and service sectors, developers and marketers are attempting to gain some perspectives about what types of RSRs they should develop and what design features should be emphasized to gain comparative advantages in their adoption. When business adopted e-commerce and internet technologies, the key elements of success was not only the presence of a website or e-commerce features but also the embracing of the online service quality (Lee & Lin, 2005; Zeithaml, 2002). Similar to the adoption of internet technologies, the success or failure of businesses begins with the service quality received from RSRs. In this study, the anticipated service quality is defined as overall consumer evaluation and expectation of service delivery in a store environment that employs RSRs as sales staff, service providers, and shopping assistants (Lee & Lin, 2005)

The robot's service quality is influenced by various attitudinal factors such as viewpoints toward reliability in service, willingness to assist consumers, and responsiveness to consumers' requests (Berry, Zeithaml, & Parasuraman, 1990; Lee & Lin, 2005). However, consumers tend to perceive the service quality as an overall outcome rather than the components of service (Van Riel, Liljander, & Jurriens, 2001). Thus, the construct of anticipated service quality is operationalized by describing consumers' anticipation of overall service excellence such as "overall, I would be pleased with the services provided by the retail service robot," "overall, the service quality of the retail service robot is excellent," and "overall, the retail service robot would meet my expectations of what makes a good retailer."

Advances in robotic technologies have brought retailers and service providers an opportunity to incorporate RSRs into the delivery of better customer service. However, getting consumers to use new robot technologies in service environments turns out to be more difficult than having a new machine for employee use (Curran & Meuter, 2005). The literature shows that the anticipation of service quality is closely related to consumers' positive attitudes toward a product and a brand and ultimately helps consumers to make their purchase or use decision (Cronin & Taylor, 1992; Curran & Meuter, 2005). Further, the psychological tendency and attitudes toward specific technologies frequently influence the outcome of the task, such as the overall service quality and the behavioral intention to use the technologies (Beer et al., 2011; Curran & Meuter, 2005; Davis, 1989). From these findings, the researcher makes an assumption that when people have favorable attitudes toward HRI, they will be more likely to anticipate greater service quality from a RSR. In other words, when people feel more comfortable talking to a RSR and interacting with it, they anticipate greater future satisfaction toward the quality of service in the store environment. Based on the above, the researcher hypothesizes H3.

Hypothesis 3: Consumers' attitudes toward HRI will positively influence their anticipation of the service quality provided by a RSR.

Retail Service Robot Acceptance

Studies on technology acceptance have evolved to reflect various types of new technologies, and a great deal of interdisciplinary research has tested commonly used technology acceptance models such as Davis's (1989) TAM model, Venkatesh et al.'s (2003) UTAUT model, and the Chain model (Goodhue & Thompson, 1995). However, the acceptance of RSRs is different from other technologies in that consumers might perceive them as a social actor with human-to-human type communication (de Graaf et al., 2015). The RSR acceptance in this study is defined as the behavioral intention or inclination to use a RSR in the future when it is available in a store (Davis, 1989; Davis et al., 1989). The construct measures the strength of one's intention to use a RSR such as "I intend to use the retail service robot in the future," and "I plan to use the retail service robot in the future."

Considering the social capability of a RSR, it is necessary to understand the optimal direction of how to design, promote, operate, and manage the RSR to form consumers' attitudes toward interaction (Curran & Meuter, 2005). In the TAM model, Davis (1989) postulates that users' attitudes toward the system are a key element of technologies acceptance whether the user intends to use it or not. While the TAM model has been extensively used to explain technologies adoption, it theorizes that users' attitudes toward technologies significantly influence their behavioral intention of use, and the same relationship can be applied to attitudes toward HRI and intention to use RSRs. Furthermore, attitudinal research such as the theory of planned behavior (Ajzen, 1991; Fishbein & Ajzen, 1975) indicates that behavioral intention is strongly and directly affected by one's attitudes, and the attitude-intention relationship is widely used to assess the acceptance of technologies (Celik & Yesilyurt, 2013; Chen & Granitz, 2012; Cheung & Vogel, 2013; Davis, 1989). Therefore, if users perceive the facilitators of a RSR confidently, they are more likely to form a positive feeling about using a RSR or a robotic system. This will ultimately influence the consequences of their adoption behavior toward robots (Chau, 1996; Dabholkar & Bagozzi, 2002). To draw a greater possibility of consumer acceptance, constructing positive HRI attitudes might be the answer to the successful integration of RSRs into retail and service industries. Thus, the researcher posits the hypothesis 4.

Hypothesis 4: Consumers' attitudes toward HRI will positively influence their acceptance of a RSR.

The expected service quality is commonly proposed to influence the intention to use the technologies (Curran & Meuter, 2005; Dabholkar, 1996; Ding, Hu, & Sheng, 2011). The service quality has also emerged as one of the strong predictors of consumer satisfaction in technology use (Calisir, Altin Gumussoy, Bayraktaroglu, & Karaali, 2014; Ravindran, 2015). While consumers might not base their judgment on the acceptance of RSRs solely on their expectation of the service quality, the researcher speculates that their attitudes toward HRI might influence their anticipation of the service quality that they will receive in the near future and therefore their overall intention to use the RSR. This anticipation of future service quality should influence the acceptance of RSRs which is operationalized as behavioral intention to use. Based on the close relationship between the overall service quality and the behavioral intention to use the technologies (Beer et al., 2011; Curran & Meuter, 2005; Davis, 1989), the researcher foresees that connecting HRI to the quality of service and to acceptance will provide a strategic implication for companies that plan to adopt robots. Therefore, the researcher hypothesizes H5.

Hypothesis 5: Consumers' anticipation of the service quality provided by a RSR will positively influence their acceptance of the RSR.

In summary, this research aims to explore the psychological perceptions and attitudes toward RSRs and to build a theoretical model of acceptance as an initial step to supporting the development of RSRs in retail and service environments. The theoretical model of this study consists of the six facilitators (i.e., usefulness, intellectual intelligence, social intelligence, social expressivity, humanlikeness, and attractiveness), an inhibitor of the pre-existing anxiety toward robots, and the attitudes toward HRI as a central mediator that will eventually influence the anticipation of service quality and acceptance. Figure 2 presents the theoretical model of RSR acceptance.

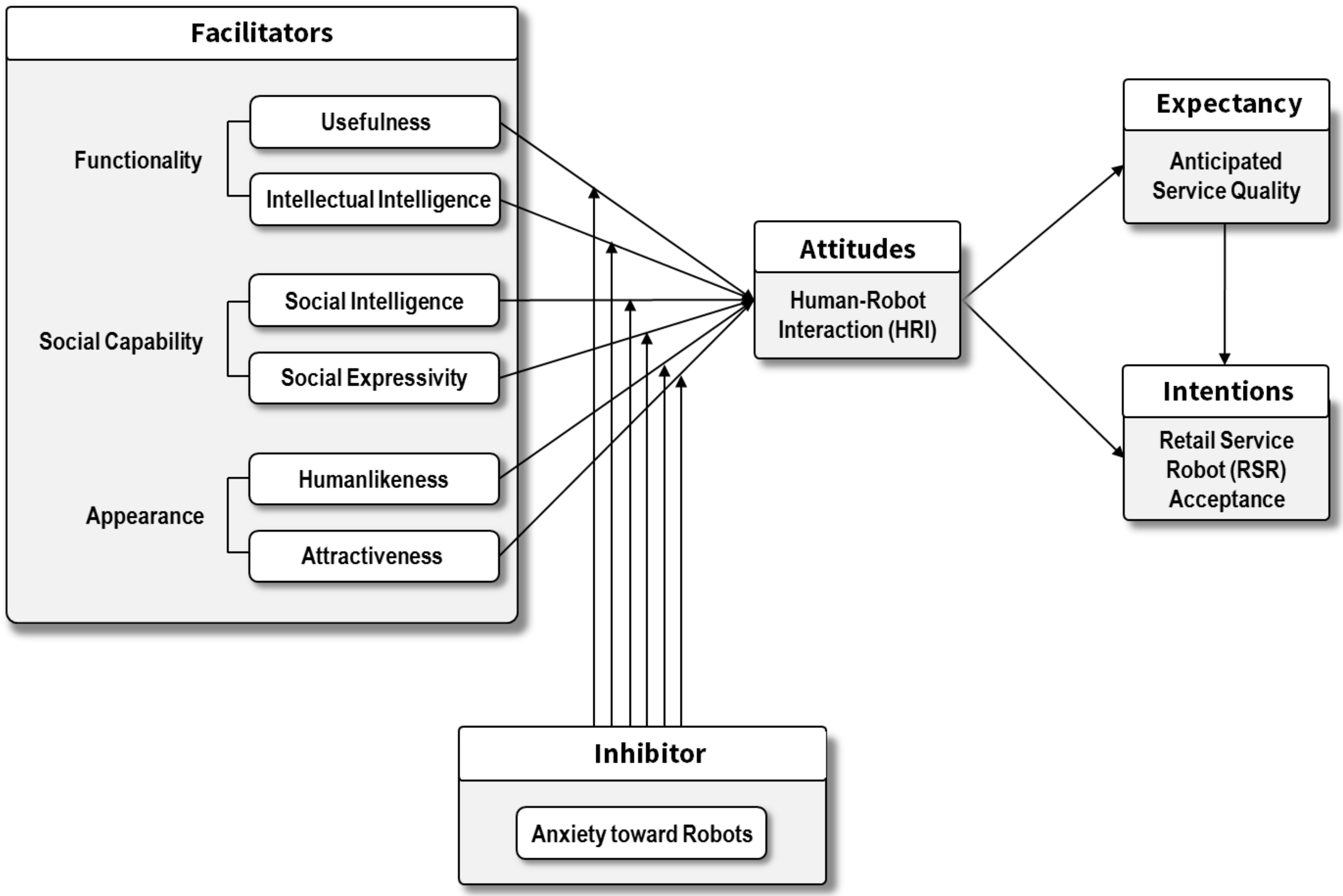


Figure 2. A theoretical model of Retail Service Robot Acceptance.

CHAPTER III
METHODS

This chapter explains the methodological approaches and procedures. The chapter consists of three sections. The first section describes the research design, the research model, and hypotheses. The second section explains the focus group and personal interviews, two pretests, and the content analyses for the development of the video clip stimuli and survey items. Lastly, the third section describes the procedures for the main test, measures, and data analysis. The video clip stimuli and survey items for the main study are developed over several steps. The main study was exempted from a review of human subjects by the Institutional Review Board (IRB) at the University of Tennessee, Knoxville (IRB No. UTK IRB-16-03046-XP, see Appendix A).

Research Design

Given that this study is designed to build a theoretical model of acceptance and to investigate the role of consumers' anxiety and HRI attitudes toward robots, the research uses four methodological strategies: (1) incorporating a focus group and personal interviews, (2) using a presentation method of video clip stimuli, (3) empirical data collection and multigroup SEM analyses, and (4) the application of three key product categories for the model's generalization. Figure 3 presents the flow of this study research and Table 3 provides a purpose for each stage in the flow. Since general consumers are not familiar with RSRs, the researcher adopts the use of video clips as stimuli, which enables viewers to be informed about RSRs and to evoke future behavioral intentions on the specific situation that they are not

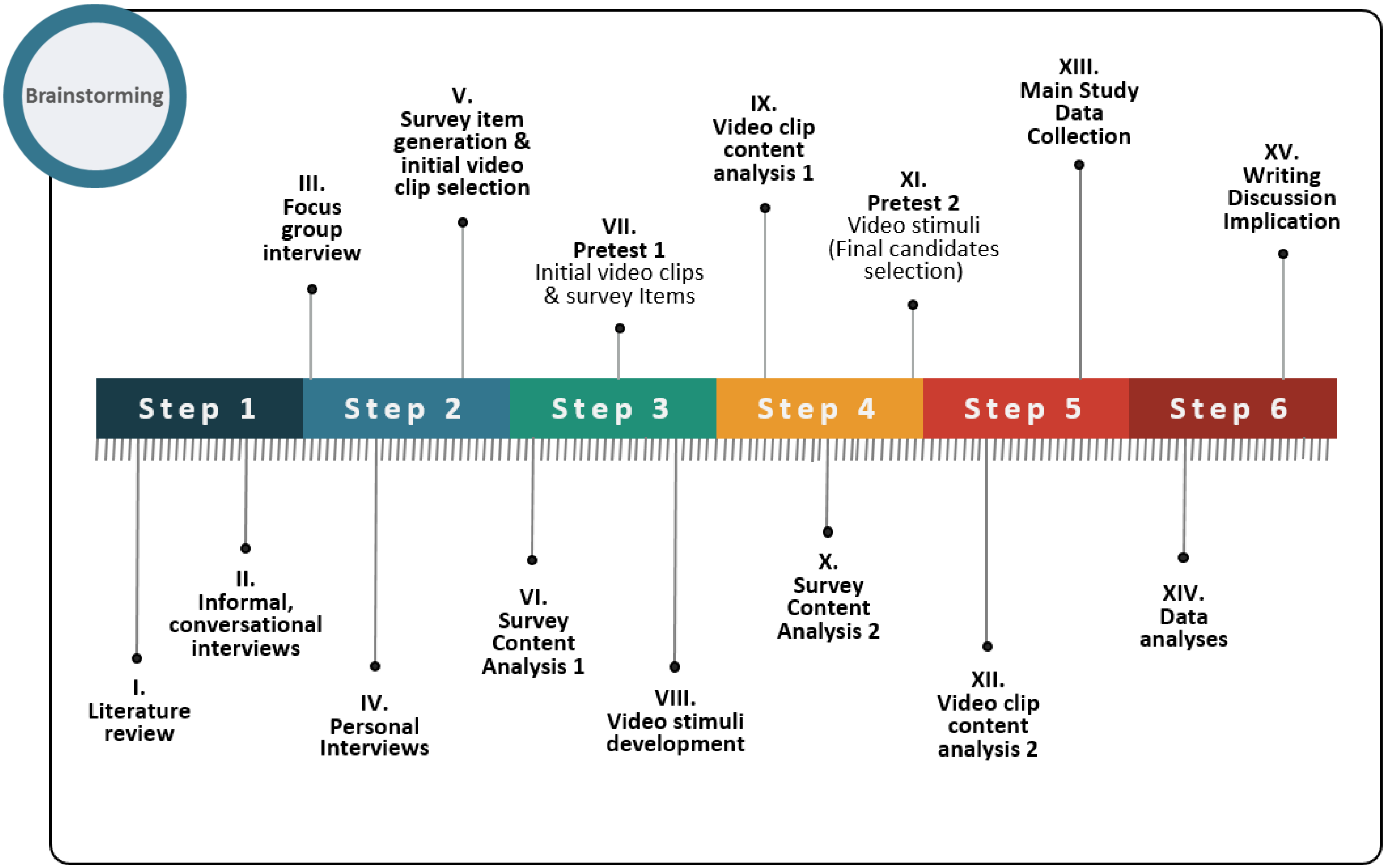


Figure 3. Research flow.

Table 3. The purpose of each step in the research flow.

		Research flow	Purpose
		Brainstorming for the research idea generation	
Step 1	I.	Literature review	Review of current literature to provide a theoretical background for the study.
	II.	Informal/conversational interviews	Conduct unstructured and informal interviews to generate hypotheses to be investigated.
Step 2	III.	Focus group interview	Conduct a focus group to explore the meaning of RSRs and influential factors of human interaction with robots.
	IV.	Personal interviews	Conduct in-depth personal interviews to identify perceptions, opinions, beliefs, and attitudes toward RSRs and HRI.
	V.	Survey item generation & initial video clip selection	Generate preliminary study constructs and survey items and select initial video clips to be available online.
Step 3	VI.	Survey content analysis 1	Conduct a content analysis on preliminary survey items.
	VII.	Pretest 1	Pre-check study variables, survey items, and video clips' content using a convenient student sample.
	VIII.	Video stimuli development	Create video clip stimuli and scripts based on feedback from the focus group, personal interviews, and Pretest 1.
Step 4	IX.	Video content analysis 1	Conduct a content analysis on initial video clip stimuli.
	X.	Survey content analysis 2	Conduct a second content analysis on scale items for refining the survey instrument.
	XI.	Pretest 2	Evaluate video clip stimuli and select final candidates for the main study.
Step 5	XII.	Video content analysis 2	Select final video clip stimuli and product categories for the main study.
	XIII.	Main study data collection	Collect data for the main study.
Step 6	XIV.	Data analyses	Conduct data analyses and hypotheses testing.
	XV.	Writing Dissertation /Discussion/Implication	Complete writing of dissertation with discussion, implications, and limitations.

familiar with. Moreover, using the video clip stimuli makes the research scenario more engaging and interactive for participants as they mirror real-life situations (Petr, Belk, & Decrop, 2015). At this early stage of RSR adoption in business, the researcher recognized the necessity of a focus group and personal interviews to explore consumers' responses concerning interactions with RSRs and their perspectives on the acceptance of robot technologies.

Research Model

This study tests a conceptual model that illustrates the relationship among perceived facilitators, attitudes toward HRI, anxiety toward robots, anticipated service quality, and behavioral intentions. The proposed model depicts the moderating effect of pre-existing anxiety toward robots on the relationship between consumers' perceived facilitators and their attitudes toward interaction with RSRs in response to video clip stimuli. The facilitators consist of functionality, such as usefulness and intellectual intelligence; social capability, such as social intelligence and social expressivity; and appearance, such as humanlikeness and attractiveness. The researcher hypothesizes that these perceived facilitators positively influence consumers' attitudes toward HRI as a central mediator that affects the degree of anticipated service quality and acceptance measured as the behavioral intention to use robots. Most importantly, the researcher hypothesizes that the effect of the perceived facilitators on consumers' attitudes toward HRI is weaker when their preconditioned anxiety is higher. Table 4 depicts the summary of proposed hypotheses and Figure 4 presents the hypothesized research model of acceptance.

Table 4. Summary of research hypotheses.

Hypotheses		**Path**
H1	$H1_a$	Usefulness → Attitudes toward HRI
	$H1_b$	Intellectual intelligence → Attitudes toward HRI
	$H1_c$	Social intelligence → Attitudes toward HRI
	$H1_d$	Social expressivity → Attitudes toward HRI
	$H1_e$	Humanlikeness → Attitudes toward HRI
	$H1_f$	Attractiveness → Attitudes toward HRI
H2	$H2_a$	Anxiety toward robots → − (Usefulness → HRI)
	$H2_b$	Anxiety toward robots → − (Intellectual intelligence → HRI)
	$H2_c$	Anxiety toward robots → − (Social intelligence → HRI)
	$H2_d$	Anxiety toward robots → − (Social expressivity → HRI)
	$H2_e$	Anxiety toward robots → − (Humanlikeness → HRI)
	$H2_f$	Anxiety toward robots → − (Attractiveness → HRI)
H3	H3	Attitudes toward HRI → Anticipated service quality
H4	H4	Attitudes toward HRI → RSR acceptance
H5	H5	Anticipated service quality → RSR acceptance

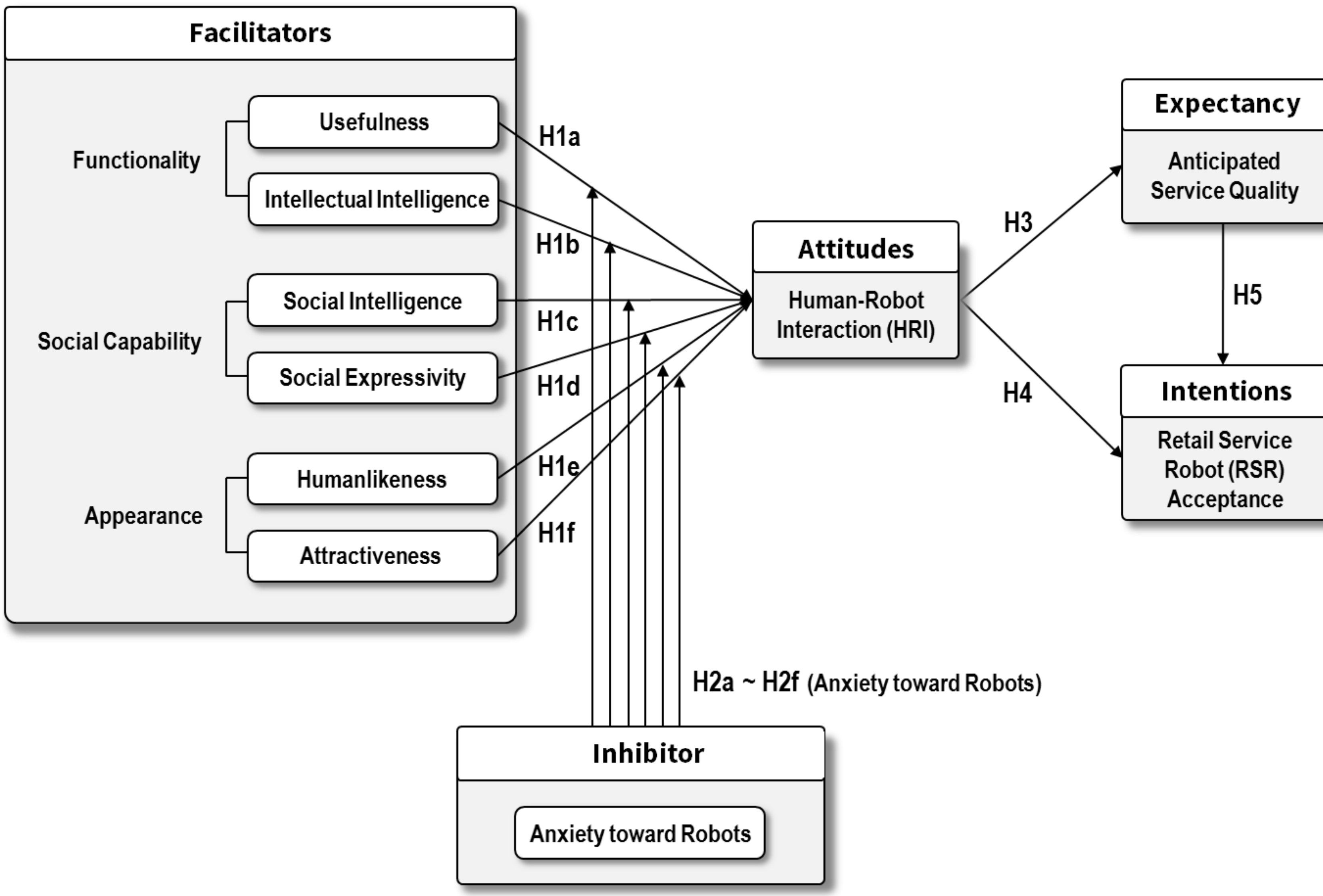


Figure 4. A hypothesized research model of Retail Service Robot acceptance.

Focus Group and Personal Interviews

To support the hypotheses, the research process conducted unstructured informal interviews with three faculty members at two major southeastern universities as a preliminary step (*n* = 3). Figure 5 depicts this preliminary process.

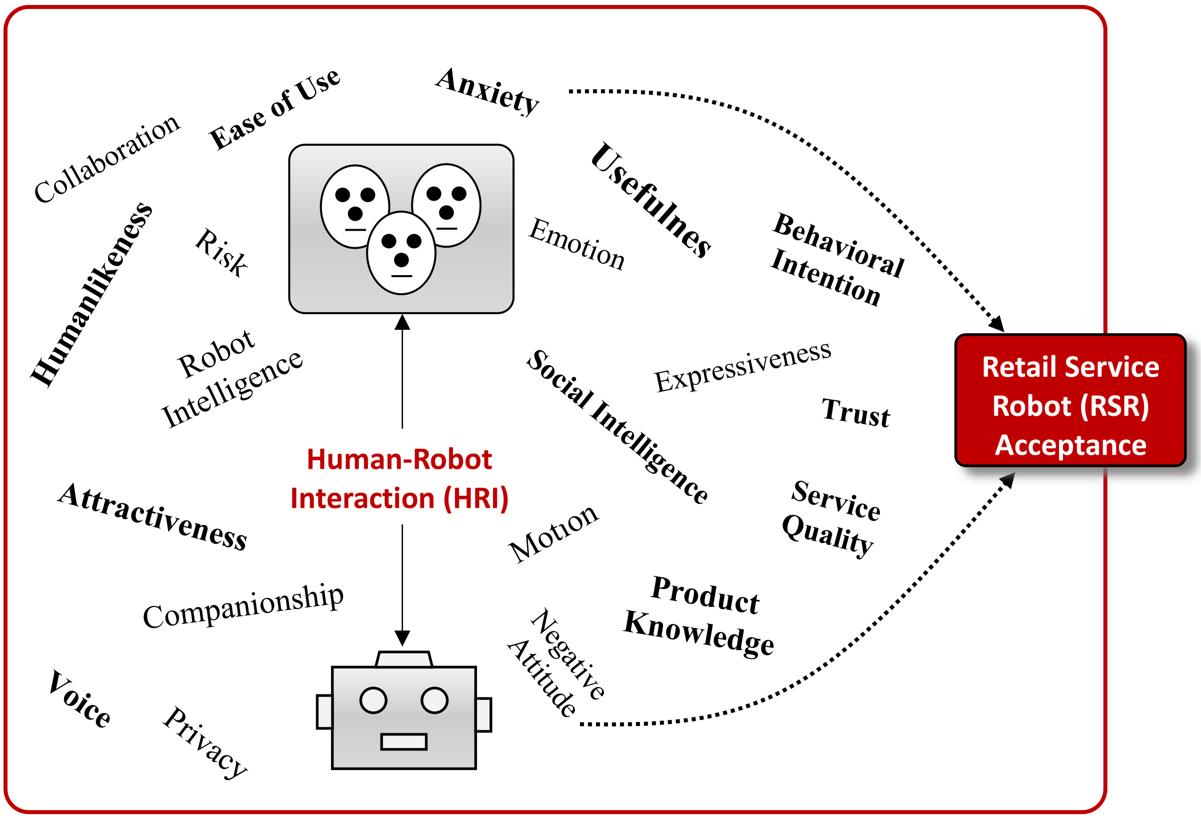


Figure 5. A preliminary process for modeling acceptance of Retail Service Robots.

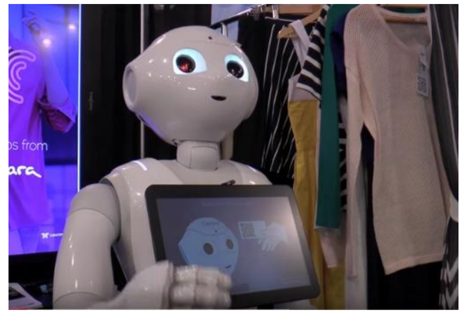
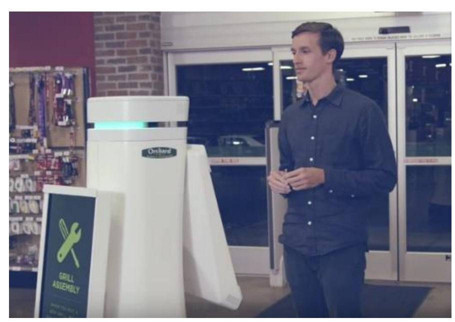
Next, this research interviewed the focus group to gain multiple perspectives in a group setting of college students in retail and consumer sciences enrolled at a major southern university (*n* = 12). In-depth personal interviews of another sample associated with the same university followed the focus group to reconfirm perceptions, opinions, beliefs, and attitudes toward HRI and the RSRs (*n* = 17): 11 college students and 2 graduate students with various majors, 2 faculty members, and 2 university staff members with college degrees. Among these participants, 5 interviewees were male and 11 interviewees were female. The interviews started with a greeting and an expression of gratitude for participation. Interviewees were informed that participation is voluntary and that the information obtained from the interview would be kept confidential. Interviewees were fully informed of the details of the RSRs before questions were asked. All interviews were voice-recorded and notes were taken. Table 5 presents a script for the focus group and personal interviews.

In the video screening and searching process, the researcher and a faculty member selected eight initial video clips in four product categories from available online contents: fashion, small kitchen appliance (coffee machine), technology (mobile phones), and household hardware products (see Table 6). The focus group was shown video clip set A (n = 12) and the personal interviewees were shown either the same set A (n = 9) or set B (n = 8). The two sets contain comparable video content with slight variability for quality and dialogues. Both video clip sets A and B include four video clips in four product categories. After showing them video clips, participants were asked six open questions about their perceptions of RSRs, attitudes toward interaction with robots, and potential facilitators and moderators of HRI. The interviewees provided their opinions on the robot's characteristics, potential influencers of HRI, and the acceptance of RSRs. In terms of functionality, participants generally had positive views about the robots' performance such as providing useful information, saving time, helping with purchases, and finding products easily. Regarding the social capability of RSRs, participants found the robots to be mostly friendly, helpful, and communicative. Concerning the appearance of RSRs, participants were attracted by the humanlike design and voice of the robots. However, participants also expressed their concerns about the malfunctions of the robot, the privacy risk,

Table 5. The script for the focus group and personal interviews.

Question	Interview Script
Introductory Script	Today I am going to show you several video clips about retail service robots. I am interested in your opinions of robots and what you think about them. After learning about the current issues in retail service robots and watching videos, I will ask you several questions about your thoughts on the retail service robots presented in the video clips. Because I am interested in what you think, there are no right or wrong opinions.
Question 1.	What characteristics or elements of robots do you think a retail service robot should have?
Question 2.	If you are in a retail store that uses a retail service robot, how and when do you use it?
Question 3.	Tell me about your positive perception or feeling about the retail service robot.
Question 4.	Tell me about your negative perception or feeling about the retail service robot.
Question 5.	What would influence your decision to interact with the retail service robot in the store?
Question 6.	What would influence your decision not to use the retail service robot in the store?

Table 6. Online video clip contents: a focus group, personal interviews and pretest 1.

Service	Video clip set A.	Video clip set B.
Fashion	 https://www.youtube.com/watch?v=29ecYdLhC8s	 https://www.youtube.com/watch?v=1fQ1uf-Obms
Kitchen Appliance	 https://www.youtube.com/watch?v=FGbc-G1lTaU	 https://www.youtube.com/watch?v=cggWYWXxrNI
Mobile phones	 https://www.youtube.com/watch?v=V1mZ7_kZppM	 https://www.youtube.com/watch?v=RFWfHd_zY3Y
Household Hardware	 https://www.youtube.com/watch?v=i_zTcVKz3oQ	 https://www.youtube.com/watch?v=Sp9176vm7Co

and their discomfort in having a conversation with the RSRs. The interviewees' responses to facilitating and inhibiting factors were summarized and categorized in Table 7. Overall, video clip set A was evaluated as better than set B in terms of video quality, voice quality and loudness, human interactivity, and uniform structure. The feedback mentioned that the background music in the video clips should be removed from the content to avoid possible media effects that might generate positive responses from the viewers. This recommendation led to the creation of eight new video clips for the main study.

Pretest 1

The purpose of pretest 1 was to pre-check the selected variables and survey items in the research model and to choose video clips as stimuli for the main test. Based on the literature review and interviews, the researcher selected six facilitating factors and the moderating factor of anxiety toward robots, developed survey measurement items, and proposed the research model with a total of ten constructs (Figure 4). Among the two sets of video clips, set A is initially selected for running a pretest based on the feedback from the focus group (Table 6). The measures are adapted and modified from existing scales to reflect our research context (see Measures section). Prior to pretest 1, a content analysis of the preliminary survey items was conducted by two faculty members and two graduate students in the consumer science and robotic psychology fields. The survey items were revised for clarity and readability based on these researchers' comments. For pretest 1, 20 key items were included in the survey as shown in Appendix B.

A convenience sample of 33 undergraduate students in retail and consumer sciences enrolled at a major southern university participated in pretest 1. Participants were asked to

Table 7. Summary of interviews (focus group and personal interviews).

Facilitators	Outlined items provided by interviewees
Functionality	
Usefulness	• Answering my question efficiently • Helping to avoid waiting in long lines • Fast information delivery • Finding items easily • Convenient to use • Purchase item quickly • Processing the payment quickly • Useful product information • Receiving decent service where I might not necessarily expect a good quality of service
Intellectual Intelligence	• Providing accurate information • Trustworthy and reliable information • Providing information for making the best purchase decision • Providing information for making a difficult purchase decision on high-priced products
Social Capability	
Social Intelligence	• Robot seems to be nice to interact with • Speaking or answering appropriate things • Being able to interact with
Social Expressivity	• Sounds friendly • Seems to be communicative • Speaking like a human sale associate • Seems to be conversational
Appearance	
Humanlikeness	• Human-like characteristics • Elegant movement like humans • Thought process like humans • Human-like voice • Human-like body components
Attractiveness	• Appealing robot appearance • Innovative robot design and look with tablet • Attractive color of the robot • Unattractive robot shape and movement

Table 7. Summary of interviews (focus group and personal interviews) (continued).

Inhibitor	Outlined Themes
Anxiety toward Robots	Discomfort in using robots Discomfort in using new technologies Discomfort of having a real conversation with a robot Discomfort of receiving a robot's opinion Distrust in a robot's performance Too artificial Feeling insecurity staying with robots only Feeling discomfort staying with robots only Anxiety of losing control in my decisions Anxiety of replacing human labor Discomfort about revealing personal information Risk of revealing financial or credit card information Discomfort about being asked to provide personal information Cannot trust a robot Privacy risk

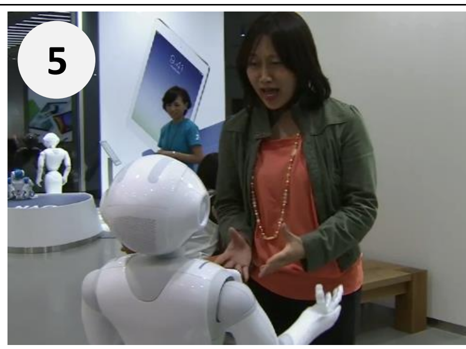
complete the pretest survey, write down their comments on the study variables and survey items, and to provide an overall opinion of the RSRs in the video clips. On the basis of pretest 1, the survey items and video clips were revised further. Instead of using two types of RSRs, “Pepper” was recommended for all stimuli development. Due to this reason, among the four product categories (fashion, small kitchen appliance, technology, and household hardware), the video clip with household hardware was changed to the clip with food products (restaurant setting). Because the video contents were available online, editing the specific commercial or brand content was requested, and re-recording the foreign language in English was recommended. In the fashion video clip A, editing the robot’s dialogues and opinions (a robot’s judgments) that were too personal or subjective was recommended to avoid potential bias that might create negative perceptions toward robots. These recommendations were reflected in the eight new video clips for the main study.

Video Clip Stimuli for the Main Study

Based on feedbacks from the focus group, personal interviews, and the pretest 1, eight video stimuli were created for the final selection process for the main test. The video clip stimuli comprise four product categories: fashion (apparel), small kitchen appliances (coffee machines), technology (mobile phones), and food products (restaurant setting). Two video clips were developed for each product category. First, the script for the eight video clips was developed as described in Appendix C-1 to C-8. Using this script, the researcher recorded the dialogues using volunteer voice actors or actress. The video contents were edited and the written cover/introductory pages were inserted at the beginning of the video clips. For the fashion category, a subcategory of footwear (woman's shoes) was added. Next, the contents of these eight videos were analyzed by three faculty members in the consumer sciences field.

To minimize any potential bias or media effects, the background music was removed for all video clips. Further, the store brand name was edited to avoid brand familiarity, and the contents were restructured to make logical sense. The subjective opinions of robots were edited to make the content more informative, and an identical written introduction was added to all video clips. Then the model of mobile phone in the technology video clip was updated to a newer version, and the price of the food ordered in the restaurant video clip was changed to reflect a reasonable market price. A comparable video and audio quality for all eight video clips were maintained, and the above revisions of the video clips as well as their script were made before conducting pretest 2 and the final stimuli selection process for the main study. Table 8 presents the details of the eight video clips developed for pretest 2.

Table 8. Eight video clip stimuli development for pretest 2.

Service	Video clip set A.	Video clip set B.
Fashion (apparel & footwear)	 Video Run Time: 1 min 54 seconds	 Video Run Time: 1 min 08 seconds
Small Kitchen Appliance (coffee machine)	 Video Run Time: 1 min 10 seconds	 Video Run Time: 1 min 34 seconds
Technology Product (Mobile phone)	 Video Run Time: 1 min 25 seconds	 Video Run Time: 1 min 13 seconds
Food product (Restaurant)	 Video Run Time: 1 min 24 seconds	 Video Run Time: 1 min 17 seconds

Pretest 2

The purpose of pretest 2 is to select the four video stimuli among the eight videos created for conducting the main test. A jury of seven researchers consisting of both faculty members and graduate students majoring in consumer sciences examined the eight video clips to select the final set of stimuli for the main test. The jury (n = 7) used the 5-point rating scale ranging from excellent (5) to bad (1), to evaluate the eight video clips for overall quality, human interactivity, and appropriateness. The jury was also asked to provide a written evaluation on each video clip. The results indicated that stimuli 1, 3, 5, and 7 were comparably better suited for the study's purpose as well as overall video quality and content appropriateness (Table 9).

Table 9. Pretest 2 video clip stimuli evaluation.

Stimuli No.	Product Category	Total Run Time	5-point Rating Mean Scores
1	Fashion (apparel)	1 minute 54 seconds	**3.86***
2	Fashion (shoes)	1 minute 08 seconds	3.57
3	Small kitchen appliance	1 minute 10 seconds	**4.14***
4	Small kitchen appliance	1 minute 34 seconds	2.57
5	Technology (mobile phone)	1 minute 25 seconds	**3.71***
6	Technology (mobile phone)	1 minute 13 seconds	2.29
7	Food (restaurant setting)	1 minute 24 seconds	**3.57***
8	Food (restaurant setting)	1 minute 17 seconds	2.86

Note. * Video clips selected as final candidates for the main study.

The mean score of 5-point rating scale was 3.32 out of 5. Video clips of 2, 4, 6, and 8 were underrated mostly because of dubbing issues or unmatched timing with the re-recorded voice, background setting such as Japanese brand signage on the wall, and awkward store atmosphere in the video clips. Finally, an introductory recorded voice accompanied by subtitles was added before the written/image title slide. The content of the introductory narration is included in the script for the video clips in Appendix C-1 to C-8.

After pretest 2, a second video content analysis was conducted by a jury that consisted of three faculty members to reconfirm the final candidates. Based on their recommendations, the video clip with small kitchen appliance (video no. 2) was dropped due to a potential bias from its well-known store brand (i.e., Nescafé store) and the other three video clips were kept for the main study. The calories and nutrition information in the food product category (video no. 7) was revised to be more accurate. Further, the length of the introduction with subtitles was shortened and the biased or promotional content was eliminated. Table 10 presents the images of the final video clips for the main data collection.

Table 10. Final video clip stimuli selected for the main test.

Fashion	**Technology**	**Food**
		
Run time: 2 mins 03 secs	Run time: 1 min 38 secs	Run time: 1 min 37 secs

Main Test

This section explains the survey procedures, measurement items, and data analysis for the main test. The researcher conducted the main test using an online survey of US consumer panelists at a market research agency. The main test used the three video clips selected after pretest 2 and the two video content analyses.

Survey Procedure and Participants

The researcher used Qualtrics to create the web-based online survey. A market research agency, Research Now (formerly known as e-Rewards), recruited the participants via an email invitation to complete a survey hosted by a major university in the southeast region of the United States. The company distributed the online survey to their consumer panels for 12 days, and received a total of 1,424 responses. The survey started with an introduction to the study, an informed consent, and a screening question that asks about the age of the participants (Appendix D). The participants had to be 18 years or older. Using Qualtrics' survey termination setting, the participants that were less than 18 years of age were redirected to a web page with a custom thank you message and their surveys were terminated.

The participants were randomly assigned to one of the three video clips followed by the questionnaire. As a result, the study groups had the same chance of being assigned to a given video stimulus, which ensured an approximately equal sample size for each video clip of a product category (Cook & Campbell, 1979). To achieve a balanced mixture of age, gender, ethnicity, income, and regions that represent general US consumer groups (ideally reproducing US National Census demographic data), the researcher audited the demographic proportion of the data-in-process daily throughout the entire data collection period of 12 days. After excluding 62 incomplete and careless responses, 1,362 out of 1,424 collected responses were retained.

Appendix D presents the final survey for the main test.

Table 11 shows the demographic details of respondents (n = 1,362). The analysis of respondents' demographic information showed that gender was evenly distributed (52.9% were female). The age ranged from 18 to 87 years old, with a median age of 41. Approximately 61.6% were employed, either full-time or part-time. The participants were widely distributed along the income spectrum, with the median annual household income between $60,000-$79,999. The majority of participants were Caucasians (61.6%), followed by African-Americans (14.0%) and Hispanics and Latino-Americans (14.0%). The participants' dispersal by region (states) was well balanced throughout all 52 states, following the US population distribution (Northeast 20.2%; Midwest 22.0%; South 35.2%; West 22.5%).

Measures

The instrument was designed to measure nine variables of consumers' perceptions of RSRs, attitudes toward HRI, and the behavioral intention to use RSRs. All items of these variables were measured on a 7-point Likert-type scale, anchored by 'strongly disagree' (1) and 'strongly agree' (7). The measures of this study were modified from existing scales to reflect the study's context.

For the facilitating factors, the researcher derives the usefulness scale items from Davis (1989), intellectual intelligence scale items from Bartneck et al. (2008), social intelligence scale items from De Ruyter et al. (2005), social expressivity scale items from De Ruyter et al. (2005), humanlikeness scale items from Bartneck et al. (2008), and the attractiveness scale items from Srinivasan et al. (2002). The researcher derives the scale items for the inhibiting factor of anxiety toward robots from Nomura et al. (2006). The scale items for the attitudes toward HRI have two aspects—emotional interaction and information interaction. The emotional interaction sub-scale

Table 11. Demographic profile of respondents (n = 1,362).

Variable	%		%
Gender		**Education**	
Male	47.1	Less than high school	1.8
Female	52.9	High school graduate	25.5
		Associate degree (two-year college)	21.4
Age		Bachelor's degree	26.9
Ages 18-24	17.3	Graduate degree	23.1
Ages 25-34	17.8		
Ages 35-44	20.1	**Employment**	
Ages 45-54	16.9	Employed (full-time and/or part-time)	1.8
Ages 55-64	11.7	Student and not working	25.5
Ages 65+	16.2	Unemployed	21.4
		Retired	26.9
Annual Household Income		Homemaker	23.1
Less than $20,000	17.4	Other	2.6
$20,000-39,999	17.4		
$40,000-59,999	14.8		
$60,000-79,999	12.0	**Region**	
$80,000-99,999	14.2	Northeast	20.2
$100,000-119,999	5.9	Midwest	22.0
$120,000-139,999	2.9	South	35.2
$140,000-$159,999	4.4	West	22.5
$160,000 or more	5.4		
Race		**Marital Status**	
African-American	14.0	Married	49.9
Caucasian	61.6	Single, never married	34.5
Native American	1.2	Separated, divorced, widowed	14.3
Asian or Pacific Islander	5.9	Other	1.2
Hispanic or Latino	14.0		
Other	3.2		

items come from Nomura and Kanda (2003) and Nomura et al. (2008), and the information interaction sub-scale items come from Ko, Cho, and Roberts (2005). However, these two closely related aspects of HRI are proposed as a factor. Lastly, the scale items for the anticipated service quality are derived from Lee and Lin (2005), and the acceptance is measured by the behavioral intention to use the RSR. The scale items for acceptance are adopted from Davis (1989) and Davis et al. (1989). The researcher used the aforementioned measures for both pretest 1 and the main test. Several researchers in the consumer science field conducted two content analyses of the survey items prior to pretest 1 (survey content analysis 1) and before the main test (survey content analysis 2). The survey items were revised for clarity and readability based on these researchers' comments.

Data Analysis

To test the hypotheses proposed in this study, the researcher uses structural equation modeling (SEM) and multigroup analyses. The measurement model is validated by using an exploratory factor analysis (EFA), one-factor confirmatory factor analysis (CFA), and the Item Response Theory (IRT) that is based on an item-level analysis. Prior to building the SEM model, the researcher conducted multiple one-way ANOVAs to verify any impact from variations in three product categories on all latent constructs used in the study. After determining no significant group mean differences among the three product categories, the SEM basic model was tested. For conducting multigroup analyses, the construct of anxiety was divided into low and high groups based on two cut-off values as the followings (also see the Measurement Invariance section in the Chapter IV. Results) (Gerstman, 2014):

1) Low group cut-off = Median (4.0) - 0.25* interquartile range (1.6) = 3.6

(The low group's anxiety score < 3.6; mean score: 2.69)

2) High group cut-off = Median (4.0) + 0.25 * interquartile range (1.6) = 4.4

(The high group's anxiety score > 4.40; mean score: 5.51)

- Interquartile range (measure of variability) = 5.0 (Q3: 75%) – 3.4 (Q1: 25%) = 1.6
- *Note*: The mid-range (mean score 3.61 to 4.40) was excluded for multigroup SEM analyses.

Further, measurement invariance of the latent constructs was tested across these two groups prior to conducting the multigroup analyses.

CHAPTER IV

RESULTS

This chapter discusses the results of the main study. The researcher first tested the full SEM model with a total sample size (*n* = 1,362) to examine the relationships depicted in the research model and to assess hypotheses H1a to H5. A three-step analysis was performed to validate the measurement model. First, EFA and one-factor CFA were performed to explore the underlying factor structure of observed variables. Second, the IRT based item analysis was conducted to assess the quality of the scale items and item information. Third, the CFA with all constructs was conducted to verify the measurement model. The SEM and multigroup analysis were used to test the conceptual model that depicts relationships among the study variables. The analysis of measurement invariance in the latent constructs was conducted across low and high groups with anxiety toward robots. The IRT analysis uses IRTPRO3. EFA, CFA, SEM, and multigroup analyses use the MPlus 7.4. The parameters are estimated with the maximum likelihood method. The model fit is evaluated with the χ^2/df ratio, comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) (Hair, Black, Babin, & Anderson, 2009).

Preliminary Analysis and Evaluation

Suppressor Effect of Social Expressivity

The researcher reports the deletion of a suppressor variable for social expressivity, a sub-factor of social capability (3 items: the retail service robot appears to be expressive; the retail service robot appears to display an appropriate expression to the customer's confusion; the retail service robot seems to show signs of thinking before answering questions or fulfilling the customer's request). The evidence of the statistical suppressor effect for social expressivity was found during the preliminary measurement and structural models' evaluations and verified once again after finalizing the measurement and structural models. In the preliminary EFA and factor analyses, the scale items of social expressivity were cross-loaded on the three exogenous variables (usefulness, social capability, and appearance) and positively correlated with them (r = 0.74 – 0.82, $p < 0.001$). In the structural model evaluation, the addition of social expressivity improved the standardized path coefficients (βs) between the three exogenous variables and the attitudes toward HRI in the model: usefulness (β: 0.665 → 0.683), social capability (β: 0.169 → 0.210), and appearance (β: 0.165 → 0.251). Further, the final beta weight (β) of social expressivity to the attitudes toward HRI ($\beta = -0.140$, $p = 0.036$) was the opposite sign from its correlation with HRI ($r = 0.75$, $p < 0.001$), which is clear evidence of a net or negative suppressor (Conger, 1974; Darlington, 1968; Gaylord-Harden, Cunningham, Holmbeck, & Grant, 2010). Therefore, social expressivity was not included any more in the analysis and excluded from the study model (Conger, 1974; Darlington, 1968).

Factor Structure Evaluation

Prior to the IRT item analysis, the preliminary EFA with a Geomin rotation and the one-factor CFA were conducted to determine the factor structures of the observed variables for ten constructs: the six facilitators of usefulness, intellectual intelligence, social intelligence, social expressiveness, humanlikeness, and attractiveness; the inhibitor of anxiety toward robots; attitudes toward HRI; the anticipated service quality; and the RSR acceptance. The parameters were estimated using the maximum likelihood method (ML). From the EFA, factors with an eigenvalue greater than 1 and items with factor loading above 0.50 were included in further analyses. The cross-loaded scale items on different factors or items with factor loadings below 0.5 were omitted and scree plots were examined prior to the CFA (Hair, Black, Babin, Anderson, & Tatham, 2006). As a result, the following sets of constructs were merged to a single factor: (1) intellectual intelligence and social intelligence (eigenvalue of one factor: 5.16); (2) humanlikeness and attractiveness (eigenvalue of one factor: 4.93); (3) two sub-factors of HRI (information interaction and emotional interaction) (eigenvalue of one factor: 3.67). After deleting cross-loaded five items (SC3, SC4, AP8, HRI2, and HRI7) from the EFA, the one-factor CFA models of these combined constructs were run. For these combined constructs, all item factor loadings were greater than 0.50, ranging from 0.60 to 0.89. All one-factor measurement models provided an excellent-to-satisfactory fit to the data (Table 12): the CFI in the range of 0.92 to 0.99, the TLI in the range of 0.86 to 0.98, and the SRMR in the range of 0.014 to 0.042 (Hooper, Coughlan, & Mullen, 2008; Hu & Bentler, 1999).

Table 12. Combined constructs: Fit Indices for one-factor CFA models (n = 1,362).

Construct Factor model	Combined sub-factors	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Social capability	Intellectual intelligence Social intelligence	91.92	14	0.990	0.984	0.064 (90% C.I. 0.052 – 0.077)	0.014
Appearance	Humanlikeness Attractiveness	583.19	14	0.924	0.886	0.173 (90% C.I. 0.161 – 0.185)	0.042
Attitudes toward HRI	Information interaction Emotional interaction	326.8	5	0.931	0.863	0.117 (90% C.I. 0.102 – 0.132)	0.041

Table 13 shows the fit indices for the one-factor CFA models for the rest of the four study variables. After deleting cross-loaded two items (AN3 and AN5) from the EFA analyses for the four constructs, the one-factor CFA models of these four constructs were run. All items' factor loadings were greater than 0.50, ranging from 0.70 to 0.94. All one-factor measurement models provided the excellent-to-satisfactory fit to the data: CFI in the range of 0.99 to 0.96, the TLI in the range of 0.91 to 0.99, and the SRMR in the range of 0.004 to 0.029 (Hooper et al., 2008; Hu & Bentler, 1999). However, it should be noted that five variables (appearance, attitudes toward HRI, usefulness, anticipated service quality, and anxiety toward robots) indicated high RMSEA values (ranging from 0.117 to 0.173) due to small degrees of freedom (Hooper et al., 2008) as shown in Table 13. The SRMR values of these constructs were below 0.08 that were generally considered a reasonable fit under the circumstances of small degrees of freedom (Hu & Bentler, 1999): appearance (SRMR = 0.042), attitudes toward HRI (SRMR = 0.041), usefulness (SRMR = 0.008), anticipated service quality (SRMR = 0.012), and anxiety toward robots (SRMR = 0.029). Through the preliminary measurement analyses, the researcher found seven unidimensional factors (usefulness, social capability, appearance, attitudes toward HRI,

Table 13. Fit indices for one-factor CFA models (*n* = 1,362) (continued).

Construct Factor model	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Usefulness	43.724	2	0.993	0.979	0.121 (90% CI. 0.091 – 0.153)	0.008
Anticipated service quality	0.00	2	0.988	0.965	0.144 (90% CI. 0.129 – 0.192)	0.012
RSR acceptance (Intention to use)	16.28	2	0.998	0.993	0.072 (90% CI. 0.043 – 0.107)	0.004
Anxiety toward robots	139.70	5	0.956	0.911	0.141 (90% CI. 0.121 – 0.161)	0.029

anticipated service quality, RSR acceptance, and anxiety toward robots) for building the consumers' acceptance model of RSRs.

Items Analyses Using Item Response Theory

The researcher conducted the Item Response Theory (IRT) analyses to assess the quality of the scale items and the amount of information that each item provides by examining the item discrimination parameters (*a* parameter; slope; analogous to a factor loading), the item information estimates (how useful or precise in discriminating among participants), and the item threshold parameters (*b* parameter; item difficulty index) (Baker, 2001; DeMars, 2010). Items with low *a* parameter values are quite impractical or non-functional similar to the items with low factor loadings or with the low item-to-total correlations. In IRT, the item information corresponds to a reliability of an item which depends upon *a* parameter value (Baker, 2001). The item threshold or difficulty parameter (*b* parameter) relates to the respondents' ability which indicates whether an item is easy or difficult to endorse to a particular category of an item. An item with a low *b* parameter value denotes that the item is easy to endorse, and vice versa. In other words, the threshold parameter (*b*) illustrates "the proficiency at which about 50% of the respondents are expected to answer the scale item correctly" (DeMars, 2010, p. 5). Similar to z-scores, the value of *b* parameter range from -3 to +3. To explain further, an item AN1 that measures anxiety toward robots ("I would feel anxious about whether the retail service robot might talk about irrelevant things in the middle of a conversation") and that is answered with the most positive response option (b_6: transition from "agree" to "strongly agree") would be positioned to the right or higher end of the *b* parameter values (closer to +3 theta range)—respondents would find difficult to completely agree with the statement or to endorse to the "Strongly agree" option. However, if respondents possess highly anxious characteristics overall, they would be more likely to have a 50% likelihood of endorsing the most positive response option (b_6: transition from "agree" to "strongly agree") for the anxiety questions than a respondent with a lower level of anxious personality (Yang & Kao, 2014).

These psychometric properties of scale items measured by the IRT analyses are theoretically sample-invariant (e.g., gender, age, education, socioeconomic status, ethnic sample differences). In other words, even if the survey is run with different samples (participants with different demographics), the IRT analysis' results will always be the same if the assumptions of IRT are met (i.e., unidimensionality, local independence, and the response that can be modeled by a mathematical item response function) (Christopher, Charoensuk, Gilbert, Neary, & Pearce, 2009; Van Dam, Earleywine, & Borders, 2010).

The researcher ran a series of IRT analyses to select items for concise constructs and for an optimized measurement of simplicity while maintaining measurement precision (De Ayala, 2013; DeMars, 2010). High Cronbach's alphas (range of 0.86 to 0.96) and composite reliabilities (range of 0.91 to 0.96) supported the unidimensionality of each factor, meeting the assumption of IRT (De Ayala, 2013). Based on the 7-point Likert scaled items, each scale item was analyzed using Samejima's (2016) graded response model (GRM). The response scale of all items ranged from strongly disagree (1) to strongly agree (7). The results of IRT analyses indicated that the values of item discrimination parameters (a_i) range from 1.53 to 6.14, which indicated high to very high discrimination that reconfirms the desirable unidimensionality of each construct (Baker, 2001). The threshold parameters (b_i) tended to range widely across the trait continuum (range: -3.53 to 1.92). Six items exhibited slightly positive skew (UF2, SC5, SC6, SC7, HRI1, HRI4) indicating that respondents are slightly less likely to endorse lower response options (strongly disagree or disagree). Overall, most b_i parameters across the trait continuum for each item displayed relatively low item difficulty (DeMars, 2010). All IRT item parameters are shown in Tables 14. The easiest item to endorse for each construct is written bold font.

Tables 15 presents the amount of information for each item and its percentage of total scale information. The figure of information in these tables is the sum of information across all six trait levels. Most of the scale items displayed mid- to high amounts of information for each construct's criterion. Those items that provide relatively high levels of information (% total information) are written in bold in the following table. The items of UF2, AP3, HRI2, and SQ1 correspond to relatively low percentages in the total information within the scale construct, which indicates a little contribution to the scale utility (Appendix E-1 to E-7) (Van Dam et al., 2010). These three items either display comparatively low values of the discrimination parameters (a_i) within each construct or cross-loaded. Through the IRT analyses, the researcher took out three items because of their failure to better match the data structure (e.g., low item information; relatively low *a* parameters; cross-loaded): UF2 from usefulness, AP3 from appearance, and SQ1 from anticipated service quality. The cross-loaded item HRI2 was initially omitted from the attitudes toward HRI during EFA and factor structure evaluation and it was also identified as having low *a* parameter value with low item information.

In sum, the researcher purifies the measures by diagnosing and omitting uninformative items or items with low values of the discrimination parameters. To support the selection process of final items, the researcher uses visual aids of a combined item characteristic curve (ICC) which merges ICC with item information functions (IIF) (Appendices E-1 to E-7). In ICC, the steepest point of the curve is the function of *a* parameter. The higher the *a* parameter is, the steeper the curve is and the more discriminating the item (Baker, 2001; DeMars, 2010). Finally, Table 16 presents the summaries of the factor structure evaluation and the IRT analyses.

Table 14. Item Response Theory (IRT) parameter estimates (*n* = 1,362).

Construct	Cronbach's α	Item#	*a*	b_1	b_2	b_3	b_4	b_5	b_6
Usefulness	0.957	UF1	4.45	-2.07	-1.60	-1.27	-0.62	0.03	0.91
		UF2*	***2.91***	-2.31	-1.79	-1.30	-0.68	0.10	1.18
		UF3	4.56	-1.75	-1.28	-0.93	-0.24	0.28	1.06
		UF4	4.84	-1.89	-1.43	-1.08	-0.35	0.25	1.00
		UF5	4.77	-1.79	-1.32	-0.91	-0.22	0.35	1.17
		UF6	4.52	-1.85	-1.39	-0.96	-0.30	0.28	1.02
Social Capability	0.940	SC1	3.82	-2.30	-1.98	-1.77	-1.06	-0.26	0.80
		SC2	4.14	-2.40	-2.06	-1.85	-1.21	-0.30	0.71
		SC5	3.26	-2.47	-2.12	-1.73	-0.97	-0.07	0.99
		SC6	2.93	-2.71	-2.33	-1.96	-1.23	-0.32	0.87
		SC7	3.31	-2.42	-2.20	-1.92	-1.18	-0.43	0.71
		SC8	3.45	-2.62	-2.25	-1.91	-1.06	-0.21	0.86
		SC9	3.67	-2.59	-2.29	-1.97	-1.18	-0.38	0.68
Appearance	0.935	AP1	3.12	-1.70	-1.16	-0.60	0.01	0.55	1.38
		AP2	2.61	-1.91	-1.32	-0.70	-0.09	0.56	1.42
		AP3*	***1.53***	-3.53	-2.64	-1.92	-1.04	-0.05	1.26
		AP4	2.79	-1.86	-1.31	-0.80	-0.18	0.53	1.40
		AP5	3.90	-1.78	-1.32	-0.86	-0.08	0.51	1.27
		AP6	3.66	-2.00	-1.51	-1.04	-0.32	0.32	1.18
		AP7	4.20	-1.70	-1.26	-0.89	-0.09	0.46	1.26
Attitudes toward Human-Robot Interaction (HRI)	0.910	HRI1	3.53	-1.90	-1.46	-0.91	-0.34	0.36	1.27
		HRI2*	***2.30***	-1.87	-1.33	-0.81	0.02	0.61	1.57
		HRI3	4.85	-1.58	-1.28	-0.94	-0.33	0.27	1.04
		HRI4	2.88	-1.66	-1.15	-0.73	0.01	0.59	1.49
		HRI5	2.54	-2.35	-1.95	-1.59	-0.79	0.09	1.11
		HRI6	2.36	-2.44	-2.12	-1.67	-0.78	0.12	1.16
Anticipated Service quality	0.928	SQ1	3.61	-2.03	-1.6	-1.27	-0.56	0.21	1.05
		SQ2	4.85	-1.82	-1.48	-1.18	-0.38	0.27	1.12
		SQ3	3.76	-2.07	-1.66	-1.35	-0.48	0.27	1.08
		SQ4	5.51	-1.65	-1.33	-1.06	-0.33	0.26	1.01
Retail Service Robot (RSR) acceptance	0.962	AC1	5.87	-1.67	-1.23	-0.83	-0.05	0.49	1.10
		AC2	4.79	-1.73	-1.30	-0.99	-0.28	0.30	0.99
		AC3	5.78	-1.71	-1.23	-0.89	-0.10	0.41	1.08
		AC4	6.14	-1.70	-1.18	-0.87	-0.15	0.43	1.04
Anxiety toward Robots	0.861	AN1	2.12	-1.68	-0.87	-0.38	0.42	1.06	1.92
		AN2	2.29	-2.16	-1.42	-0.90	-0.15	0.71	1.66
		AN4	1.96	-1.55	-0.82	-0.41	0.26	0.96	1.76
		AN6	2.88	-1.84	-1.07	-0.58	0.13	0.82	1.51
		AN7	2.79	-1.59	-0.86	-0.38	0.36	1.01	1.57

Table 15. IRT item information summed across trait estimates (*n* = 1,362).

Construct		**Item**	**Information**	**% Total Information**
Usefulness	UF1	The retail service robot would be useful.	49.45	17.11%
	UF2*	The retail service robot would address my shopping needs.	***27.54***	***9.53%***
	UF3	Using the retail service robot would save me time.	50.35	17.42%
	UF4	**It would be easy to shop with the retail service robot.**	**55.68**	**19.27%**
	UF5	**Using the retail service robot would improve my shopping ability.**	**55.29**	**19.13%**
	UF6	Using the retail service robot would enhance my effectiveness during shopping.	50.68	17.54%
Social Capability	**SC1**	**The retail service robot appears to be competent.**	**38.13**	**15.93%**
	SC2	**The retail service robot seems to be knowledgeable.**	**42.72**	**17.85%**
	SC5	The retail service robot appears to listen attentively.	31.82	13.29%
	SC6	The retail service robot appears to say appropriate things.	26.18	10.94%
	SC7	The retail service robot listens without interrupting when the customer is talking.	30.16	12.60%
	SC8	The retail service robot seems to remember the detailed information about the customer's questions.	34.12	14.25%
	SC9	**The retail service robot appears to be polite.**	**36.23**	**15.14%**

Table 15. IRT item information summed across trait estimates (*n* = 1,362) (continued).

Construct		Item	Information	% Total Information
Appearance	AP1	The retail service robot looks natural.	29.74	13.93%
	AP2	The retail service robot appears humanlike.	23.21	10.87%
	AP3*	The voice of the retail service robot is humanlike.	***9.36***	***4.38%***
	AP4	The retail service robot moves in a humanlike way.	25.51	11.95%
	AP5	**The retail service robot is attractive.**	**41.70**	**19.53%**
	AP6	**The retail service robot looks visually appealing.**	**38.47**	**18.02%**
	AP7	**The retail service robot is good looking.**	**45.49**	**21.31%**
Attitudes toward Human-Robot Interaction (HRI)	**HRI1**	**I would feel relaxed talking with the retail service robots.**	**36.34**	**20.75%**
	HRI2*	I would feel comforted being with the retail service robots that appear to have emotions.	***19.02***	***10.86%***
	HRI3	**I would enjoy interacting with retail service robots.**	**52.68**	**30.08%**
	HRI4	I would feel pleasure having a conversation with retail service robots.	26.17	14.94%
	HRI5	Talking to the retail service robot would help me learn about a product.	21.56	12.31%
	HRI6	Using the retail service robot would be a good way to do research with new products.	19.35	11.05%
Anticipated service quality	***SQ1****	My overall opinion of the services provided by the retail service robot is very good.	***36.54***	***18.87%***
	SQ2	**Overall, I would be pleased with the services provided by the retail service robot.**	**54.85**	**28.33%**
	SQ3	Overall, the service quality of the retail service robot is excellent.	39.15	20.22%
	SQ4	**Overall, the retail service robot would meet my expectations of what makes a good retailer.**	**63.06**	**32.57%**

Table 15. IRT item information summed across trait estimates (*n* = 1362) (continued).

Construct		Item	Information	% Total Information
Retail Service Robot (RSR) acceptance	**AC1**	**I intend to use the retail service robot in the future.**	**72.89**	**26.64%**
	AC2	I predict I would use the retail service robot in the future.	53.24	19.46%
	AC3	**I plan to use the retail service robot in the future.**	**70.72**	**25.84%**
	AC4	**I am likely to use the retail service robot in the future.**	**76.79**	**28.06%**
Anxiety toward Robots	AN1	I would feel anxious about whether the retail service robot might talk about irrelevant things in the middle of a conversation.	16.96	16.38%
	AN2	I would feel anxious about whether the retail service robot might not be flexible in following the direction of our conversation.	19.81	19.13%
	AN4	I would feel anxious about how I should talk to the retail service robot.	14.20	13.72%
	AN6	**I fear that using a retail service robot would reduce the confidentiality of my personal information.**	**27.36**	**26.43%**
	AN7	**Using the retail service robot would infringe on my privacy.**	**25.20**	**24.34%**

Table 16. Summary of factor structure and item analyses (*n* = 1362).

Construct		Item	Factor loading	Item adoption	Remark
Usefulness	UF1	The retail service robot would be useful.	0.89	○	
	UF2	The retail service robot would address my shopping needs.	0.81	–	Relatively low ***a*** parameter: IRT low item information;
	UF3	Using the retail service robot would save me time.	0.90	○	
	UF4	It would be easy to shop with the retail service robot.	0.91	○	
	UF5	Using the retail service robot would improve my shopping ability.	0.91	○	
	UF6	Using the retail service robot would enhance my effectiveness during shopping.	0.91	○	
Social Capability (One factor)	**Intellectual Intelligence**				
	SC1	The retail service robot appears to be competent.	0.84	○	
	SC2	The retail service robot seems to be knowledgeable.	0.86	○	
	SC3	The retail service robot seems to be responsible.	0.61	–	Cross-loaded
	SC4	The retail service robot looks sensible.	0.58	–	Cross-loaded
	Social Intelligence				
	SC5	The retail service robot appears to listen attentively.	0.83	○	
	SC6	The retail service robot appears to say appropriate things.	0.82	○	
	SC7	The retail service robot listens without interrupting when the customer is talking.	0.79	○	
	SC8	The retail service robot seems to remember the detailed information about the customer's questions.	0.84	○	
	SC9	The retail service robot appears to be polite.	0.84	○	

Table 16. Summary of factor structure and item analyses (*n* = 1,362) (continued).

Construct	Item		Factor loading	Item adoption	Remark
Appearance (One factor)	**Humanlikeness**				
	AP1	The retail service robot looks natural.	0.82	○	
	AP2	The retail service robot appears humanlike.	0.77	○	
	AP3	The voice of the retail service robot is humanlike.	0.60	–	Relatively low ***a*** parameter: IRT low item information
	AP4	The retail service robot moves in a humanlike way.	0.79	○	
	Attractiveness				
	AP5	The retail service robot is attractive.	0.88	○	
	AP6	The retail service robot looks visually appealing.	0.87	○	
	AP7	The retail service robot is good looking.	0.89	○	
	AP8	The retail service robot has a good appearance.	0.69	–	Cross-loaded
Attitudes toward HRI (One factor)	**Emotional Interaction**				
	HRI1	I would feel relaxed talking with the retail service robots.	0.83	○	
	HRI2	I would feel comforted being with the retail service robots that appear to have emotions.	0.67	–	Cross-loaded; Relatively low ***a*** parameter: IRT low item information
	HRI3	I would enjoy interacting with retail service robots.	0.88	○	
	HRI4	I would feel pleasure having a conversation with retail service robots.	0.78	○	

Table 16. Summary of factor structure and item analyses (*n* = 1362) (continued).

Construct	Item		Factor loading	Item adoption	Remark
Attitudes toward HRI (One factor)	**Information Interaction**				
	HRI5	Talking to the retail service robot would help me learn about a product.	0.82	◯	
	HRI6	Using the retail service robot would be a good way to do research with new products.	0.80	◯	
	HRI7	Using the retail service robot would help me learn about useful product information.	0.79	–	Cross-loaded
Anticipated service quality	SQ1	My overall opinion of the services provided by the retail service robot is very good.	0.86	–	Cross-loaded; Relatively IRT low item information
	SQ2	Overall, I would be pleased with the services provided by the retail service robot.	0.91	◯	
	SQ3	Overall, the service quality of the retail service robot is excellent.	0.86	◯	
	SQ4	Overall, the retail service robot would meet my expectations of what makes a good retailer.	0.93	◯	
Retail Service Robot (RSR) acceptance (Intention to use)	AC1	I intend to use the retail service robot in the future.	0.94	◯	
	AC2	I predict I would use the retail service robot in the future.	0.91	◯	
	AC3	I plan to use the retail service robot in the future.	0.93	◯	
	AC4	I am likely to use the retail service robot in the future.	0.94	◯	

Table 16. Summary of factor structure and item analyses (*n* = 1362) (continued).

Construct		Item	Factor loading	Item adoption	Remark
Anxiety toward Robots	AN1	I would feel anxious about whether the retail service robot might talk about irrelevant things in the middle of a conversation.	0.78	○	
	AN2	I would feel anxious about whether the retail service robot might not be flexible in following the direction of our conversation.	0.78	○	
	AN3	I would feel anxious about whether the retail service robot might understand difficult conversation topics.	0.78	–	Cross-loaded
	AN4	I would feel anxious about how I should talk to the retail service robot.	0.70	○	
	AN5	I would feel anxious about whether I would understand what the retail service robot is talking about.	0.80	–	Cross-loaded
	AN6	I fear that using a retail service robot would reduce the confidentiality of my personal information.	0.73	○	
	AN7	Using the retail service robot would infringe on my privacy.	0.74	○	

Normality Test

The univariate normality of the data is assessed by the skewness and kurtosis of each scale item as well as the composite score of each construct. The absolute values of skewness range from 0.09 to 1.31, and the absolute values of kurtosis range from 0.02 to 2.46, which are within the threshold value of ±3.0 and indicate satisfactory univariate normality for all scale items and constructs (Hoyle, 1995) (Table 17).

Multicollinearity Test

Multicollinearity among the three variables (i.e., perceived usefulness, social capability, and appearance that predict attitudes towards HRI in SEM model) was assessed by running a series of multiple linear regressions. Variance inflation factor (VIF) is examined as shown in Table 18. The VIF scores range from 1.67 to 2.63, which are within the threshold value of 10.0 and indicate multicollinearity is not identified in the data (Neter, Kutner, Nachtsheim, & Wasserman, 1996).

Measurement Model Assessment

The results of the CFA indicate that the final measurement model shows satisfactory fit indices: χ^2 (390) = 3094.64, $p < 0.001$; CFI = 0.942; TLI = 0.936; RMSEA = 0.071 (90% C.I.0.069 – 0.074); SRMR = 0.038 (Hooper et al., 2008; Hu & Bentler, 1999; MacCallum, Browne, & Sugawara, 1996; Steiger, 2007). All items measured on a 7-point Likert-type scale were treated as continuous variables in CFA. All items have standardized factor loadings that range from 0.775 to 0.936. The construct validities of the latent constructs are evaluated with convergent and discriminant validities. The convergent validity is confirmed by these findings: (a) all path weights are significant ($p < 0.001$) (Hair et al., 2009), (b) the composite reliabilities

Table 17. Assessment of normality.

Construct/Items	Mean	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Usefulness	4.91	1.45	-0.71	0.07	0.09	0.13
UF1	5.21	1.48	-0.95	0.07	0.62	0.13
UF3	4.80	1.64	-0.60	0.07	-0.28	0.13
UF4	4.94	1.56	-0.68	0.07	0.03	0.13
UF5	4.73	1.60	-0.57	0.07	-0.27	0.13
UF6	4.87	1.60	-0.62	0.07	-0.20	0.13
Social Capability	5.58	1.04	-1.04	0.07	1.87	0.13
SC1	5.53	1.27	-1.21	0.07	1.97	0.13
SC2	5.64	1.19	-1.26	0.07	2.46	0.13
SC5	5.39	1.25	-0.95	0.07	1.30	0.13
SC6	5.61	1.18	-1.18	0.07	2.09	0.13
SC7	5.67	1.22	-1.31	0.07	2.43	0.13
SC8	5.54	1.18	-0.98	0.07	1.51	0.13
SC9	5.69	1.17	-1.16	0.07	2.07	0.13
Appearance	4.59	1.41	-0.43	0.07	-0.20	0.13
AP1	4.39	1.71	-0.27	0.07	-0.77	0.13
AP2	4.48	1.66	-0.32	0.07	-0.67	0.13
AP4	4.56	1.64	-0.45	0.07	-0.48	0.13
AP5	4.60	1.58	-0.43	0.07	-0.30	0.13
AP6	4.87	1.53	-0.63	0.07	-0.02	0.13
AP7	4.62	1.61	-0.50	0.07	-0.27	0.13
Human-robot interaction	4.89	1.30	-0.59	0.07	0.28	0.13
HRI1	4.77	1.55	-0.57	0.07	-0.19	0.13
HRI3	4.83	1.64	-0.67	0.07	-0.13	0.13
HRI4	4.37	1.69	-0.33	0.07	-0.65	0.13
HRI5	5.24	1.37	-0.94	0.07	1.07	0.13
HRI6	5.23	1.34	-0.88	0.07	1.02	0.13
Anticipated service quality	4.95	1.43	-0.75	0.07	0.13	0.13
SQ2	4.93	1.56	-0.77	0.07	0.13	0.13
SQ3	5.03	1.45	-0.74	0.07	0.13	0.13
SQ4	4.88	1.63	-0.73	0.07	0.13	0.13
RSR Acceptance (Use Intent)	4.72	1.56	-0.66	0.07	-0.05	0.13
AC1	4.62	1.64	-0.50	0.07	-0.28	0.13
AC2	4.87	1.65	-0.72	0.07	-0.08	0.13
AC3	4.69	1.64	-0.56	0.07	-0.27	0.13
AC4	4.70	1.65	-0.58	0.07	-0.26	0.13

Table 17. Assessment of normality (continued).

Construct/Items	Mean	SD	Skewness	SE of Skewness	Kurtosis	SE of Kurtosis
Anxiety toward robots	4.12	1.35	-0.06	0.07	-0.33	0.13
AN1	3.89	1.70	0.01	0.07	-0.84	0.13
AN2	4.56	1.54	-0.47	0.07	-0.27	0.13
AN4	3.96	1.83	-0.06	0.07	-1.02	0.13
AN6	4.26	1.64	-0.16	0.07	-0.69	0.13
AN7	3.96	1.70	0.05	0.07	-0.74	0.13

Table 18. Multicollinearity test (VIF).

Independent variables entered	Dependent variables entered		
	Usefulness	Social capability	Appearance
Usefulness	–	2.626	1.998
Social capability	1.666	–	1.998
Appearance	1.666	2.626	–

of all constructs range from 0.910 to 0.962, meeting the minimum criteria of 0.70 (Nunnally & Bernstein, 1994), and (c) the values of average variances extracted (AVEs) for all latent variables are greater than the threshold value of 0.50 (Fornell & Larcker, 1981), ranging from 0.670 to 0.864. A total of 30 final scale items is included in measuring the hypothesized relationships of the structural model. Figure 6 illustrates the CFA model and Table 19 presents the final measures for the main survey.

The discriminant validity is evaluated with the AVE values, which are greater than the shared variance (i.e., squared correlation coefficients) between all possible pairs of latent variables (Fornell & Larcker, 1981). As shown Table 20, the construct of attitudes toward HRI

CFA Model Fit:
χ^2 (390) = 3094.64, p < 0.001;
CFI = 0.942; TLI = 0.936;
RMSEA = 0.071 (90% C.I.0.069 – 0.074);
SRMR = 0.038

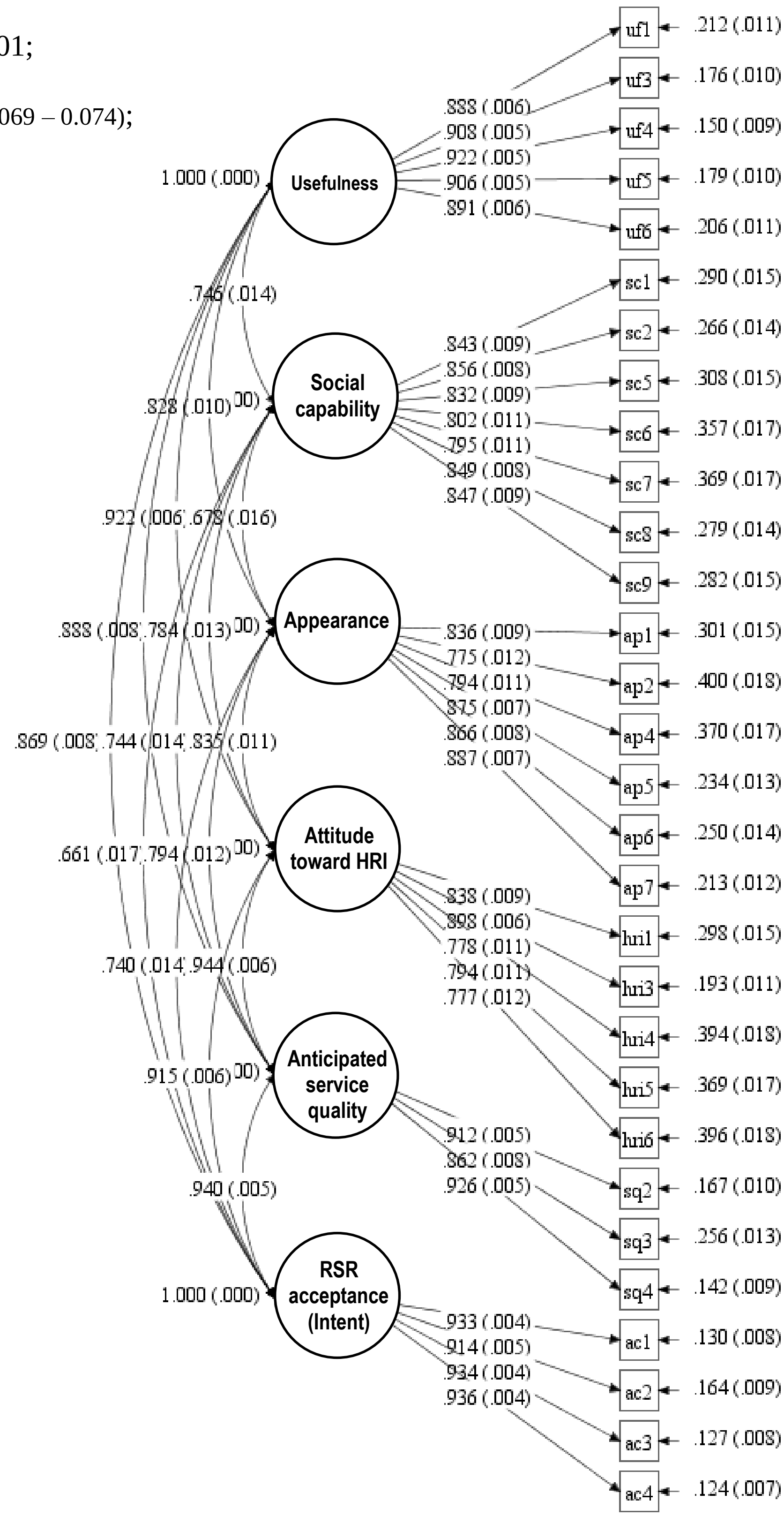


Figure 6. Confirmatory Factor Analysis (CFA) model (n = 1,362).

Table 19. Measurement items and confirmatory factor analysis.

Construct	Item#	Measurement item	Factor Loading	Composite reliability
Usefulness	UF1	The retail service robot would be useful.	0.888	0.957
	UF3	Using the retail service robot would save me time.	0.908	
	UF4	It would be easy to shop with the retail service robot.	0.922	
	UF5	Using the retail service robot would improve my shopping ability.	0.906	
	UF6	Using the retail service robot would enhance my effectiveness during shopping.	0.891	
Social Capability	SC1	The retail service robot appears to be competent.	0.844	0.940
	SC2	The retail service robot seems to be knowledgeable.	0.856	
	SC5	The retail service robot appears to listen attentively.	0.832	
	SC6	The retail service robot appears to say appropriate things.	0.802	
	SC7	The retail service robot listens without interrupting when the customer is talking.	0.795	
	SC8	The retail service robot seems to remember the detailed information about the customer's questions.	0.849	
	SC9	The retail service robot appears to be polite.	0.847	
Appearance	AP1	The retail service robot looks natural.	0.836	0.935
	AP2	The retail service robot appears humanlike.	0.775	
	AP4	The retail service robot moves in a humanlike way.	0.794	
	AP5	The retail service robot is attractive.	0.875	
	AP6	The retail service robot looks visually appealing.	0.866	
	AP7	The retail service robot is good looking.	0.887	

Table 19. Measurement items and confirmatory factor analysis (continued).

Construct	Item#	Measurement item	Factor Loading	Composite reliability
Attitudes toward Human-Robot Interaction (HRI)	HRI1	I would feel relaxed talking with the retail service robots.	0.838	0.910
	HRI3	I would enjoy interacting with retail service robots.	0.898	
	HRI4	I would feel pleasure having a conversation with retail service robots.	0.794	
	HRI5	Talking to the retail service robot would help me learn about a product.	0.777	
	HRI6	Using the retail service robot would be a good way to do research with new products.	0.778	
Anticipated service quality	SQ2	Overall, I would be pleased with the services provided by the retail service robot.	0.912	0.928
	SQ3	Overall, the service quality of the retail service robot is excellent.	0.862	
	SQ4	Overall, the retail service robot would meet my expectations of what makes a good retailer.	0.926	
Retail Service Robot (RSR) acceptance	AC1	I intend to use the retail service robot in the future.	0.933	0.962
	AC2	I predict I would use the retail service robot in the future.	0.914	
	AC3	I plan to use the retail service robot in the future.	0.934	
	AC4	I am likely to use the retail service robot in the future.	0.936	

shows poor discriminant validity from usefulness, anticipated service quality, and the acceptance because its squared root of AVE (0.82) is 0.03 less than the variance shared with usefulness (0.85), and 0.06 less than the variance shared with anticipated service (0.86), and 0.01 less than the variance shared with the acceptance (0.83). Further, it should be noted that the final dependent variable of RSR acceptance shows high correlation coefficients with the attitudes toward HRI ($r = 0.91$) and with the anticipated service quality ($r = 0.94$). The attitudes toward HRI also show high correlations with the usefulness ($r = 0.92$) and the anticipated service quality ($r = 0.94$) greater than the threshold of 0.85, which provide poor discriminant validity for these constructs (Brown, 2015). Other than these flags, the discriminant validity is satisfactory. The attitudes toward HRI is a conceptually distinct construct from usefulness, anticipated service quality, and RSR acceptance (Davis, 1989; Davis et al., 1989; Lee & Lin, 2005; Nomura & Kanda, 2003; Nomura et al., 2008). However, they are closely related to each other in this empirical data analysis. Tables 20 and 21 provide the information on the construct validity of the measurement model and the correlation coefficients among all pairs of constructs in the model.

Table 20. Construct validity of the final measurement model.

	Construct	1	2	3	4	5	6
1	Usefulness	**0.90**[a]					
2	Social capability	0.55[b]	**0.83**				
3	Appearance	0.67	0.45	**0.84**			
4	Human-robot interaction (HRI)	***0.85***	0.61	0.69	**0.82**		
5	Anticipated service quality	0.77	0.55	0.62	***0.88***	**0.90**	
6	RSR acceptance	0.74	0.44	0.55	***0.83***	0.88	**0.93**

Notes: [a] The diagonal entries show the squared root of the average variance extracted (AVE) for each construct.
[b] The off-diagonal entries represent the variance shared (squared correlation) between constructs.

Table 21. Means, standard deviations, and correlation matrix.

	Construct	Mean	SD	1	2	3	4	5	6
1	Usefulness	4.91	4.45	**1.00**					
2	Social capability	5.58	1.04	0.74	**1.00**				
3	Appearance	4.59	1.41	0.82	0.67	**1.00**			
4	Human-robot interaction	4.89	1.30	*0.92**	0.78	0.83	**1.00**		
5	Anticipated service quality	4.99	1.37	*0.88**	0.74	0.79	*0.94**	**1.00**	
6	RSR acceptance	4.72	1.56	*0.86**	0.66	0.74	*0.91**	*0.94**	**1.00**

Notes: * $r > 0.85$

Measurement Invariance

A revised 30-item model was developed, and the analysis of measurement invariance in the latent constructs was conducted across two different consumer groups who possessed low ($n = 477$) or high anxiety toward robots ($n = 502$). To make a new categorization of anxiety toward robots, the sample ($n = 1{,}362$) was divided into three groups based on the respondents' pre-existing anxiety toward robots (composite score of five items). The two cut-off values were the median (4.0) - 0.25 * interquartile range (1.6) for the low group and the median (4.0) + 0.25 * interquartile range (1.6) for the high group (Gerstman, 2014). The mid-range (from 3.61 to 4.40) was excluded from the multigroup SEM analysis ($n = 979$). To determine whether there was a statistically significant difference between the means of the two groups, a one-way analysis of variance (ANOVA) was conducted. The group mean difference between the low group ($M = 2.69$; anxiety score < 3.6) and the high group ($M = 5.51$; anxiety score > 4.40) with anxiety toward robots is statistically significant, $F(1, 977) = 3569.48$, $p < 0.001$. Table 22 presents the details for the categorization of anxiety toward robots.

Table 22. Categorization of anxiety toward robots.

Construct	Categorization	Mean	Range	Count	Percent
Anxiety toward robots	Low anxiety group [a]	2.69	1.00 – 3.60	477	35.0%
	High anxiety group [b]	5.51	4.40 – 7.00	502	36.9%
	S. total			979 [c]	71.9%
	Excluded (mid-range)	4.10	3.61 – 4.40	383	28.1%
Total				1362 [d]	100.0%

Note. [a] n = 477, low anxiety group cut-off value: median - 0.25 x interquartile range.
[b] n = 502, high anxiety group cut-off value: median + 0.25 x interquartile range.
[c] n = 979, sample size for two-way ANOVA (study 2) and multigroup analysis (study 3).
[d] n = 1,362 (all groups), median of anxiety toward robots (all groups) = 4.00

To assure the valid comparisons across two groups and to establish measurement invariance, the researcher ran a series of constrained CFA models and tested whether the differences between the models across the two groups are significant (n = 979): (1) configural invariance, (2) metric invariance, (3) intercept only invariance, and (4) scalar invariance (Muthén & Muthén, 2012). Firstly, to test for the configural invariance, two CFA models with unconstrained factor loadings and intercepts were run separately for the low group (model 1) and the high group (model 2) with anxiety toward robots. The goodness-of-fit statistics are satisfactory for each CFA model for both groups and the configural invariance is satisfied: low group (χ^2 (390) = 1594.55, $p < 0.001$; CFI = 0.924; TLI = 0.915; RMSEA = 0.079 (90% C.I. 0.076 – 0.085); and SRMR = 0.046) and high group (χ^2 (390) = 1469.99, $p < 0.001$; CFI = 0.944; TLI = 0.938; RMSEA = 0.074 (90% C.I. 0.070 – 0.078); and SRMR = 0.033). Second, to test the metric invariance between the two groups, the researcher ran a CFA model in which the factor loadings are constrained to be equal across the two groups but the intercepts vary between groups (model 3). The goodness-of-fit statistics are reasonable for the CFA model and establish a metric invariance that the respondents across two groups assign the same meaning to the latent construct in this study: χ^2 (811) = 3209.53, $p < 0.001$; CFI = 0.932; TLI = 0.927; RMSEA = 0.078 (90% C.I. 0.075 – 0.081); and SRMR = 0.079.

To test intercept only invariance, the researcher then ran a CFA model that the intercepts were constrained to be equal across groups, but the factor loadings varied between groups (model 4). Goodness-of-fit statistics were satisfactory and the intercept only invariance was established: χ^2 (810) = 3239.65, $p < 0.001$; CFI = 0.931; TLI = 0.926; RMSEA = 0.078; and SRMR = 0.044. Next, to test scalar invariance, the researcher ran a model where both the factor loadings and intercepts were constrained to be equal across the two groups (model 5). The goodness-of-fit statistics are acceptable for the CFA model and the scalar invariance was established: χ^2 (840) = 3380.87, $p < 0.001$; CFI = 0.928; TLI = 0.925; RMSEA = 0.079; and SRMR = 0.084. Table 23 provides an overview of all model estimations and the model fit.

In summary, a set of CFA models is estimated to test for the measurement invariance. The results indicate equivalence across the two comparison groups (low and high anxiety groups) for the number of factors, their factor loadings, and the levels of the underlying items (intercepts) (Muthén & Muthén, 2012; van de Schoot, Lugtig, & Hox, 2012). Although the CFI and the TLI for these models indicate satisfactory to marginally acceptable fit (CFI range = 0.924 − 0.944; TLI range = 0.915 − 0.938), the RMSEA (range = 0.074 − 0.080; see Table 23 for 90% C.I.) and SRMR (range = 0.033 − 0.084) indicates the fit could be improved (Bentler, 1990; Hooper et al., 2008; Hu & Bentler, 1999; MacCallum et al., 1996; van de Schoot et al., 2012). Further, the item analyses could enhance the measurement invariance by diagnosing which factor loadings in an item level might differ across groups.

Table 23. CFA results for testing measurement invariance (n = 979).

CFA Model	Group	χ^2	*df*	*p*	CFI	TLI	RMSEA	SRMR
Configural invariance								
Model 1	Low [a]	1594.55	390	0.000	0.924	0.915	0.080 (90% C.I. 0.076 – 0.085)	0.046
Model 2	High [b]	1469.99	390	0.000	0.944	0.938	0.074 (90% C.I. 0.070 – 0.078)	0.033
Metric invariance								
Model 3	Low/High [c]	3209.53	811	0.000	0.932	0.927	0.078 (90% C.I. 0.075 – 0.081)	0.079
Intercept only invariance								
Model 4	Low/High	3239.65	810	0.000	0.931	0.926	0.078 (90% C.I. 0.075 – 0.081)	0.044
Scalar invariance								
Model 5	Low/High	3380.87	840	0.000	0.928	0.925	0.079 (90% C.I. 0.075 – 0.081)	0.084

Note. [a] n = 477, low anxiety group cut-off value (< 3.60): median - 0.25 x interquartile range.
[b] n = 502, high anxiety group cut-off value (>4.40): median + 0.25 x interquartile range.
[c] n = 979, both low anxiety group (n = 477) and high anxiety group (n = 502).

Evaluation of Potential Impacts of Product Categories

Prior to conducting structural model and multigroup analyses, the researcher conducted multiple one-way ANOVAs to determine whether the variations in product categories (fashion, technology, and food products) of the video stimuli had any impact on the six dependent variables of usefulness, social capability, appearance, attitudes toward robots, anticipated service quality and RSR acceptance. The composite score of each construct was used to test for the group mean difference of the six dependent variables with three product category levels. Participants were classified into three groups based on the product category that they viewed in the video stimulus: fashion (n = 442), technology (mobile phone) (n = 466), and food products (n = 454). Multiple one-way ANOVAs showed that there were no significant group mean differences among the three product categories for all variables, F (2, 1,359) ranged from 0.019 to 2.270, $p > 0.05$ (p-values from 0.104 to 0.982). Accordingly, the effects of the product category were interpreted as inappreciable or insignificant for all seven latent constructs in the study. Table 24 presents the results of one-way ANOVAs along with the descriptive statistics.

Revised Research Hypotheses

Based on the results of the preliminary analyses and the measurement evaluation using the EFA and one-factor CFAs, the social expressivity was identified as a negative suppressor and was excluded from the research model. The constructs of the intellectual intelligence and the social intelligence were merged as a single factor and the humanlikeness and the attractiveness were also combined as well. Accordingly, the proposed research hypotheses were revised. Figure 7 presents the final research model:

Hypothesis 1: A RSR's facilitating factors of perceived usefulness, social capability, and appearance will positively influence consumers' attitudes toward HRI.

H1a: A RSR's perceived usefulness will positively influence consumers' attitudes toward HRI.

H1b: A RSR's perceived social capability will positively influence consumers' attitudes toward HRI.

H1c: A RSR's perceived appearance will positively influence consumers' attitudes toward HRI.

Table 24. One-way ANOVAs results (n = 1,362).

Criterion variable	Product Category	N	Mean	Total Mean	*SS*	*df*	*MS*	*F*	*p*
Usefulness	Fashion	442	4.88	4.91	0.58	2	0.29	0.14	0.872
	Technology	466	4.91						
	Food	454	4.93						
Social capability	Fashion	442	5.59	5.58	1.71	2	0.86	0.79	0.452
	Technology	466	5.54						
	Food	454	5.62						
Appearance	Fashion	442	4.70	4.59	8.98	2	4.49	2.27	0.104
	Technology	466	4.50						
	Food	454	4.57						
Attitudes toward HRI	Fashion	442	4.95	4.89	2.52	2	1.26	0.74	0.475
	Technology	466	4.84						
	Food	454	4.88						
Anticipated service quality	Fashion	442	4.94	4.95	0.76	2	0.04	0.02	0.982
	Technology	466	4.96						
	Food	454	4.95						
RSR acceptance (Intention to use)	Fashion	442	4.72	4.72	1.15	2	0.57	0.24	0.790
	Technology	466	4.75						
	Food	454	4.68						

Note. *SD* = Standard deviation, *SS* = Sum of squares; *MS* = Mean square
No significant mean differences among three product category groups with the p-value less than 0.05 are found.

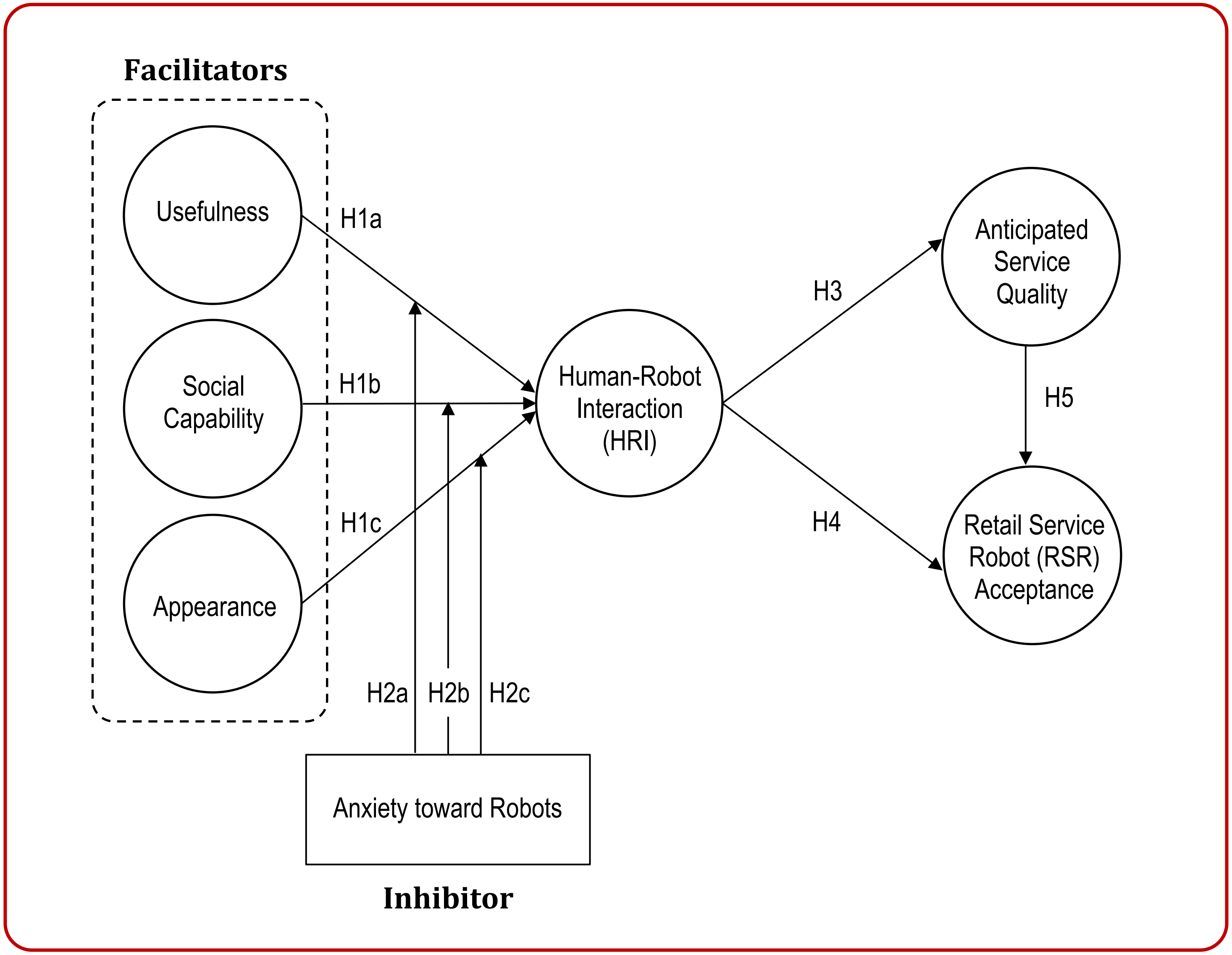


Figure 7. The revised research model of Retail Service Robot acceptance

Hypothesis 2: The effects of a RSR's facilitating factors on consumers' attitudes toward HRI is moderated by the level of their pre-existing anxiety toward robots.

H2a: The effects of the RSR's perceived usefulness on consumers' attitudes toward HRI are weaker when their anxiety about robots is higher.

H2b: The effects of the RSR's perceived social capability on consumers' attitudes toward HRI are weaker when their anxiety about robots is higher.

H2c: The effects of the RSR's perceived appearance of a RSR on consumers' attitudes toward HRI are weaker when their anxiety about robots is higher.

Hypothesis 3: Consumers' attitudes toward HRI will positively influence the anticipation of the service quality provided by a RSR.

Hypothesis 4: Consumers' attitudes toward HRI will positively influence their acceptance of a RSR.

Hypothesis 5: Consumers' anticipation of the service quality provided by a RSR will positively influence their acceptance of the RSR.

Structural Model and Multigroup Analyses

The researcher first tested the SEM basic model with the total sample (n = 1,362) to assess H1a to H5 in the revised research model. The revised model consists of three exogenous variables (usefulness, social capability, and appearance) and three endogenous variables (attitudes toward HRI, anticipated service quality, and RSR acceptance). To test the moderating effect of anxiety toward robots (H2a to H2c), a multigroup structural equation modeling approach was used to compare the low and high groups with anxiety toward robots on the factor loadings of usefulness, social capability, and appearance. The analyses of measurement invariance of the latent constructs were tested across the two groups prior to the multigroup SEM analyses.

Structural Model

A structural model examines the hypothesized relationships among constructs. Goodness-of-fit statistics are reasonable: χ^2 (396) = 3186.513, $p < 0.001$; CFI = 0.940; TLI = 0.935; RMSEA = 0.072 (90% C.I. 0.072 – 0.074); and SRMR = 0.040 (Bentler, 1990; Hooper et al., 2008; Hu & Bentler, 1999; MacCallum et al., 1996; Steiger, 2007). All path coefficients are significant ($p < .001$), which supports all hypothesized relationships (see Figure 8). Specifically, the attitudes toward HRI are significantly influenced by usefulness ($\beta = 0.674$, $p < 0.001$) (H_{1a}), social capability ($\beta = 0.158$, $p < 0.001$) (H_{1b}), and appearance ($\beta = 0.167$, $p < 0.001$) (H_{1c}). In turn, the attitudes toward HRI considerably influence both the anticipated service quality (β = 0.948, $p < 0.001$) (H_3) and the acceptance ($\beta = 0.242$, $p < 0.001$) (H_4). Further, the anticipated service quality has significant and positive effects on RSR acceptance measured by the intention to use robots ($\beta = 0.710$, $p < 0.001$) (H_5). Table 25 summarizes the testing results from the SEM basic model analysis.

Multigroup Analyses

Hypotheses 2a, 2b, and 2c posit that anxiety toward robots (inhibitor) moderates the relationship between the three facilitators (usefulness, social capability, and appearance) and the attitudes toward HRI. The researcher conducted a multigroup approach for testing the moderating effects within the SEM estimates (n = 979) (Hair et al., 2006). The researcher first

SEM Basic Model Fit:
χ^2 (396) = 3186.513, $p < 0.001$;
CFI = 0.940; TLI = 0.935;
RMSEA = 0.072 (90% C.I. 0.072 – 0.074);
SRMR = 0.040

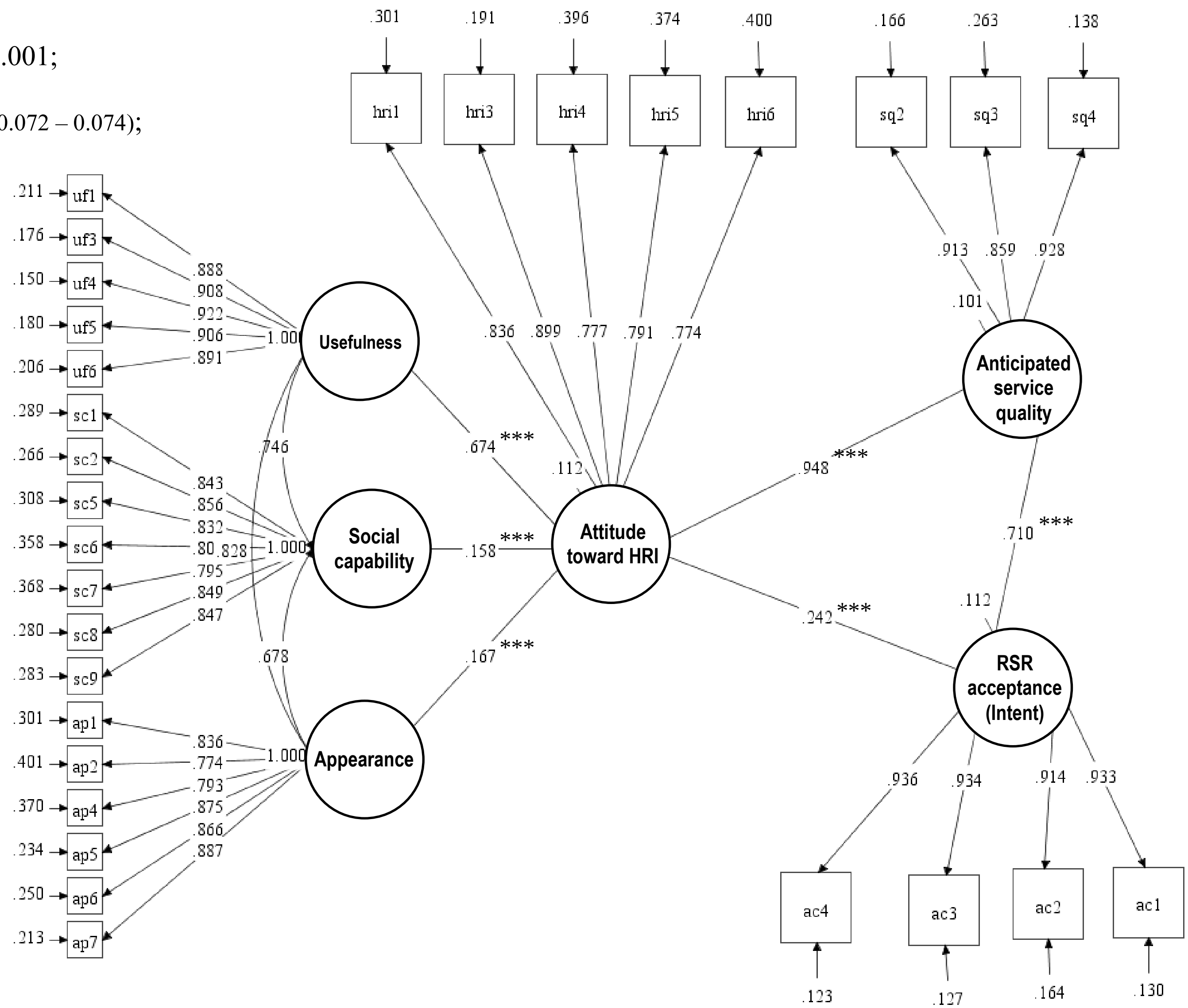


Figure 8. SEM basic model analysis (n = 1362).

Table 25. SEM basic model hypotheses testing (n = 1362).

Hypothesis	Structural Paths	Standardized Estimate	Standard Error	Est./S.E. (z-values)
H_{1a} supported	Usefulness → HRI [a]	0.674	0.026	25.820***
H_{1b} supported	Social capability → HRI	0.158	0.020	7.825***
H_{1c} supported	Appearance → HRI	0.167	0.025	6.803***
H_3 supported	HRI → Anticipated service quality	0.948	0.005	191.347***
H_4 supported	HRI → RSR Acceptance	0.242	0.058	4.141***
H_5 supported	Anticipated service quality → RSR Acceptance	0.710	0.058	12.301***

Note: [a] HRI = attitudes toward human-robot interaction;
*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

examined the overall moderating effect of anxiety toward robots by running two models simultaneously for comparison: an anchor model where all paths are free to vary across two groups and a model where three estimates of gamma (i.e., paths from three exogenous variables to an endogenous variable) are held equal across the two groups and the estimates of beta (i.e., paths between endogenous variables) are free to vary (Muthén & Muthén, 2012). The goodness-of-fit statistics of the anchor model are reasonable: χ^2 (840) = 3328.131, $p < 0.001$; CFI = 0.929; TLI = 0.927; RMSEA = 0.078 (90% C.I. 0.075 – 0.081); and SRMR = 0.050 (Bentler, 1990; Hu & Bentler, 1999; MacCallum et al., 1996; Steiger, 2007). To examine the differences in the path coefficients of the two groups, a Wald chi-square difference test of parameter constraints was assessed. If a Wald χ^2 difference with three degrees of freedom is greater than the critical value of ± 7.815 ($p < .05$), then the overall moderating effect is supported (Shanahan, Hopkins, Carlson, & Raymond, 2012). The result of the Wald chi-square test indicates that the overall moderation effect of anxiety toward robots on the relationship between the three facilitators and the attitudes toward HRI is significant: Wald χ^2 (3) = 28.604, $p < 0.001$.

The researcher then tested each constrained estimate of gamma (i.e., three paths from facilitators to attitudes toward HRI) individually for equivalency by fixing each path coefficient to be equal in each group (Muthén & Muthén, 2012). If a Wald χ^2 difference with one degree of freedom is greater than the critical value of ±3.841 ($p < .05$), then the moderating relationship is supported for each path (Shanahan et al., 2012). As shown in Table 26, the Wald χ^2 difference value associated with the relationship between social capability and attitudes toward HRI is statistically significant (Wald χ^2 (1) = 8.84, $p < .01$), which supports H2b. The Wald χ^2 difference value for the path between appearance and the attitudes toward HRI (Wald χ^2 (1) = 16.55) is also statistically significant ($p < 0.001$). While the results show the existence of the moderating effect of anxiety toward robots (H2), the direction of the moderation is opposite to H2c. Therefore, H2c is not supported. Further, there is no significant difference (Wald χ^2 (1) = 0.08, $p > .05$) in the path coefficient from usefulness to the attitudes toward HRI, which does not support H2a. It should be noted that the path coefficient from social capability to the attitudes toward HRI is greater for the low group ($\beta = 0.219$) than for the high group ($\beta = 0.045$) with anxiety toward robots, while the path coefficient from appearance to the attitudes toward HRI is greater for the high group ($\beta = 0.283$) than for the low group ($\beta = 0.070$). Table 26 presents the results of the multigroup analyses, and Table 27 summarizes the testing results for all revised hypotheses. Figure 9 illustrates the final SEM model with multigroup analysis results.

Table 26. Multigroup analyses: moderated relationship (n = 979).

Hypothesis	Paths	Wald χ^2 (df = 1)	Path coefficient (β)	
			Low group	High group
H_{2a} Not supported	Usefulness → Attitudes toward HRI	0.075	0.712***	0.695***
H_{2b} Supported	Social capability → Attitudes toward HRI	8.84***	0.219***	0.045
H_{2c} Not supported	Appearance → Attitudes toward HRI	16.55***	0.072*	0.283***

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
low anxiety group (n = 477) and high anxiety group (n = 502).

Table 27. Summary of revised research hypotheses testing.

Hypotheses		Path	Hypotheses testing result
H1	$H1_a$	Usefulness → Attitudes toward HRI	Supported
	$H1_b$	Social capability → Attitudes toward HRI	Supported
	$H1_c$	Appearance → Attitudes toward HRI	Supported
H2	$H2_b$	Anxiety toward Robots → − (Usefulness $\overset{\downarrow}{\rightarrow}$ HRI)	Not supported
	$H2_c$	Anxiety toward Robots → − (Social capability $\overset{\downarrow}{\rightarrow}$ HRI)	Supported
	$H2_c$	Anxiety toward Robots → − (Appearance $\overset{\downarrow}{\rightarrow}$ HRI)	Not supported [a]
H3	H3	Attitudes toward HRI → Anticipated service quality	Supported
H4	H4	Attitudes toward HRI → RSR acceptance	Supported
H5	H5	Anticipated service quality → RSR acceptance	Supported

Note. [a] The result of Wald χ^2 difference testing for the path between appearance and attitudes toward HRI shows the existence of the moderating effect of anxiety toward robots (H2), the direction of the moderation is the opposite to H2c. Therefore, H2c is not supported.

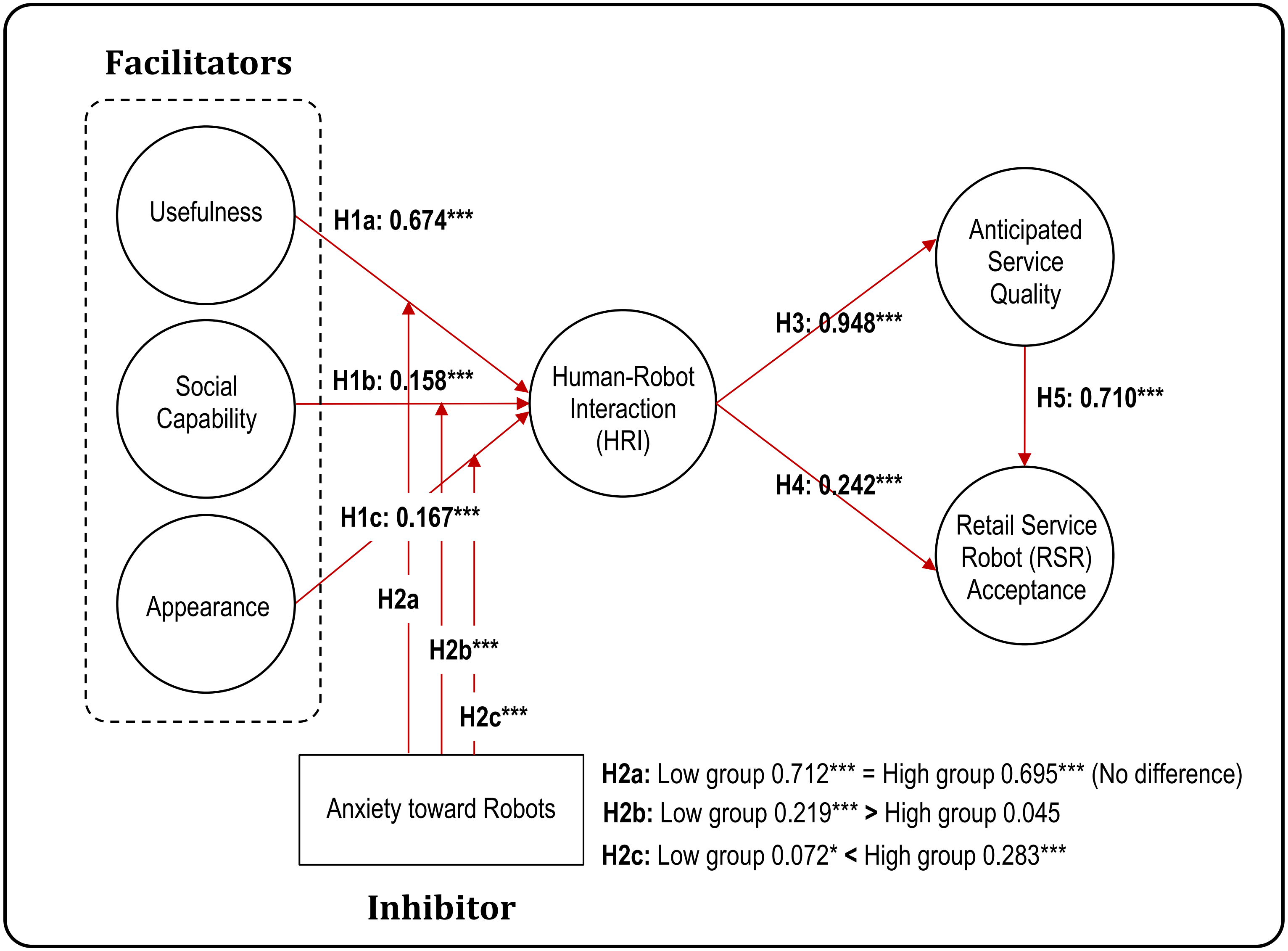


Figure 9. SEM model with analyses results

CHAPTER V
DISCUSSION AND IMPLICATIONS

The purpose of this study is to build an acceptance model for RSRs that explains the role of consumers' attitudes toward HRI and its perceived facilitators. Further, it examines how consumers' pre-existing anxiety toward robots inhibits the relationship between these facilitators and HRI. The research model is specifically for humanlike robots with AI. The researcher uses three video clips as the study stimuli to inform participants about RSRs in a real-life scenario prior to administering survey questions.

The field of HRI is a growing discipline in business research and technology application. However, companies have not made much of an effort to understand what make consumers interact with a RSR and how to effectively engage them in its adoption process. This study addresses this issue and provides a conceptual model of acceptance. This model provides valuable insights to practitioners in retail and service businesses about the future of autonomous RSRs that streamline consumer pleasant interaction with the technology and that deliver delight customer service with automation. The results suggest guidelines for RSR developers and marketers in designing more approachable RSRs that lead to successful interactions with consumers and promotes their acceptance.

First, the researcher finds that attitudes toward HRI are significantly influenced by the usefulness of a RSR. The results of this study show that consumers who perceive greater usefulness in a RSR, such as shopping effectiveness and practicality of use, are more likely to show favorable attitudes toward interaction and collaboration with the robot. They tend to feel more enjoyable and comfortable in communicating with the RSR (Bartneck et al., 2007; Nomura

& Kanda, 2003; Nomura et al., 2008). That is, consumers need to be certain that the RSR's functionality will help them conveniently shop for products and save time and effort. For this reason, companies that intend to adopt robot technology for their business must consider what tangible benefit they bring to consumers' shopping tasks (Beer et al., 2011). This finding supports the positive effect of perceived usefulness on the attitudes toward technology in past TAM models (Davis, 1989; Venkatesh et al., 2003). Being able to assist in the purchase transaction, providing reliable service, saving effort and time, and providing real-time product and stock information are examples of functional advantages in using RSRs (Barnett et al., 2014; Christensen et al., 2000). The efficiency of the RSR and its dedication to service tasks are key to generating consumers' interest in communication with robots.

Second, the researcher also finds that the social capability of a RSR has a noteworthy effect on consumers' attitudes toward HRI. The results of this study also show that participants who perceive a high level of social characteristics in a RSR are more likely to take a pleasant stance to interacting with the robot. Social capability comprises intellectual and social intelligence that enables having an appropriate conversation with a RSR (Beer et al., 2011; Kim et al., 2013). Based on the CASA and domestication theories, consumers tend to apply social rules to computers. Their attitudes and the interaction patterns with RSRs change over time. To engage consumers in long-term interactions with RSRs, the social capability of a RSR should be demonstrated when they first see the robot, even before starting the interaction. Otherwise, people could lose interest and modify their attitudes toward the robots (Leite et al., 2013). An important aspect in this HRI study is that RSRs should be designed to be socially interactive with people to elicit more willingness to share personal information and to maintain long-lasting relationships with consumers. The social skills of robots such as how they display their verbal communication, how they intellectually respond to consumers' requests, and how they articulate speech are some of the main motivations for interacting with the RSR (Nass & Moon, 2000; Nass et al., 1994).

Third, the results show that the appearance of a RSR has a strong connection with the attitudes toward HRI. Specifically, the positive perception of humanness and of a physically attractive design lead to emotionally and cognitively high levels of aptitude toward interaction with the RSR. With this finding, a RSR that bears a humanlike appearance tends to be more promising in generating user-friendly interaction with consumers than mechanical-looking robots. Finding an optimum level of physical attributes in the outer design of the robot might be beneficial in creating the consumers' confidence. However, the extent of the humanlike appearance of robots needs to be balanced with a high degree of functionality and delicate movement (Duffy, 2003). It needs to be within users' comfort zone to be perceived as approachable to communicate with. Further, a highly humanlike robot can be perceived as aggressive that produces an opposite effect where consumers might evaluate it negatively (Strait et al., 2015). In such cases, a high level of humanlikeness of a RSR does not necessarily help generate positive responses from the users but leaves a feeling of discomfort, which could be a reason that explains why people terminate their interaction with it (Lockard, 2014). Because general consumers are not familiar with RSRs yet, more research is required to investigate how to make robots' appearance that supportively influences consumers' perceptions toward RSRs in retail and service environments.

The results also show that the attitudes toward HRI increase the anticipation of service quality and the acceptance of RSRs. The anticipation of the service quality then positively influences the acceptance of RSRs. These relationships indicate a major role of HRI in integrating consumers' perception to acceptance of RSRs and to their expectancy of good service. This evaluation includes both affective and cognitive components in which the consumers feel comfortable and pleasant and enjoy learning about products through the HRI process (Beer et al., 2011; Kim et al., 2013). The affective elements include enjoyment, comfort, and pleasure having a conversation with RSRs. The cognitive elements take account of helpfulness in learning product knowledge and in assisting the product research. When consumers feel pleasant or intellectually stimulating toward interaction with the robot, they tend to predict a greater quality of service and are more likely to accept the RSRs and be determined to use it (Bartneck et al., 2007; Nomura & Kanda, 2003; Nomura et al., 2008).

The researcher also investigates whether consumers' pre-existing anxiety toward robots might inhibit the relation between perception and attitudes toward HRI in the research model. The results indicate that the relationship between the perceived social capability on consumers' attitudes toward HRI is weaker when their anxiety about robots is higher. In other words, for consumers with a low level of anxiety toward robots, their perception of the robot's social skills positively translates into their attitudes toward HRI. On the other hand, for consumers with a high level of pre-existing anxiety, their perception of social capability does not have a significant effect on their attitudes toward HRI. Hence, the social attributes of a RSR are crucial for eliciting HRI from consumers with low anxiety toward robots but not for those with high anxiety. The results also indicate that the effect of perceived appearance of a RSR on the attitudes toward HRI is greater for consumers who possess a high level of anxiety toward robots than those who retain a low degree of anxiety. While the appearance of the robots is an important predictor of attitudes toward HRI for both high and low groups, this aesthetic aspect of humanness and attractiveness is a stronger predictor for those with highly anxious feelings about robots than those with low anxiety. During the service encounters, consumers with high anxiety tend to evaluate RSRs' appearance more intensively by figuring out whether the robots will perform their task safely and whether there are any barriers to communication, thereby decreasing the probability of HRI (Nomura et al., 2004). In the development of the types and designs for RSRs, consideration of this constraint in HRI could lessen problems associated with anxiety toward robots and with the obstacles to RSR adoption.

Practical Implication

The empirical results substantiate an important link among the consumers' attitudes toward HRI, perceived facilitators, anticipated service quality, and the acceptance of RSRs. From a practical standpoint, the study provides some useful suggestions for retail and service companies that plan to adopt RSRs. First, this study provides a strategic guideline for designing RSRs that has great potential to engage consumers in the interaction that will lead them closer to purchase decisions or positive marketing outcomes. Among the three facilitators of usefulness, social capability, and the appearance of RSRs, usefulness is the strongest predictor of consumers' attitudes toward HRI regardless of their anxiety toward robots. In designing RSRs, retailers and manufacturers must focus on giving robots beneficial functions that provide shopping assistance such as finding products efficiently, taking orders and serving guests at a restaurant, helping in purchase transactions, providing physical assistance for the elderly, and offering personalized recommendations (Barnett, Foos, et al., 2015).

Second, the study calls attention to the roles of RSRs' social capability and appearance in HRI. In a retail and service environment, the RSR's role has evolved from a mechanical helper to a social communicator that shows aspects of social intelligence and humanlikeness (Fong, Nourbakhsh, & Dautenhahn, 2003). The robot's social cues and its attractive appearance increase consumers' expectations of the robot's performance and the quality of service that they will receive (Beer et al., 2011). For example, a robot server at a restaurant is expected to be socially communicative while it serves food and drinks and processes the payment (Mathur & Reichling, 2016). With regards to HRI, the researcher thus suggests that when companies consider adopting RSRs in their business, they should develop RSRs with enhanced social competence (e.g., human cognition, intellectual intelligence, and social awareness) with a humanlike design (e.g., physical humanness and socially acceptable design) that will likely increase the interactions with their consumers.

Because of the unfamiliarity with robot technologies and the negative media exposure, consumers might be unwilling to give private information to robots, such as credit card or bank information, because of distrust in the RSRs' functionalities (Nomura et al., 2008). While greater anxiety toward robots does not necessarily lead to disapproval of RSRs, companies should actively promote their use of RSRs via mass media to increase familiarity with the robots and to reduce any reluctance toward interacting with robots. In sum, when designing RSRs, companies must find the right mix of functionality, intelligence, social capability, desirable appearance, and humanlikeness to generate consumers' trust and willingness to interact with RSRs (Kamide, Kawabe, Shigemi, & Arai, 2014).

The findings from this study indicate that overall, there is a negative effect from the anxiety toward robots on the relationship between facilitators and attitudes toward HRI. When an innovative technology is introduced, consumers frequently feel anxiety, discomfort, and apprehension when using it that is similar to the way people display some level of computer anxiety (Celik & Yesilyurt, 2013; Nomura & Kanda, 2003). Such an anxiety has frequently been identified as a major cause of technology avoidance (Celik & Yesilyurt, 2013). Thus, understanding the anxiety toward robots would help retailers in lessening its negative impact or in choosing educative actions to promote HRI. Because consumers' anxiety toward robots can be reduced by exposing them to RSRs, companies should hold educational promotion events and robotic training that help to reduce the fear of robots in consumers. When consumers build some familiarity with robots, they will feel a sense of security with respect to humanlike robots and will be more likely to interact with them (Kamide et al., 2012).

The results of the multigroup analyses also indicate that RSRs' social capability is a strong predictor of the attitudes toward HRI for consumers who possess low anxiety toward robots, but not for those who hold high levels of anxiety. For consumers with low anxiety, adopting RSRs with greater communication capabilities and verbal responsiveness will help them form a human-to-robot social relationship that increases the believability of robots (Kim, Park, & Kwon, 2007). Further, RSRs' appearance has a significant effect on the attitudes toward HRI for both high and low anxiety groups, but the level of the effect is stronger for those with high anxiety. When consumers do not have much experience or information about a RSR, their overall anxiety toward the robot will most likely increase. The researcher expects that consumers with such negative preconceptions will be more resistant to changes in robotics and industrial automation. According to the CASA and the domestication theories, consumers evaluate the attractive and humanlike appearance of robots in the same way as human-to-human communication in social scenarios. Further, the most visible and accessible information about robots' proficiencies is the aesthetic design (Hegel, 2012). Especially for consumers with high anxiety toward the robot, companies should attempt to present the robots with an optimal appearance that is consistent with its social capability and functionality. The researcher recommends designers of RSRs to avoid too much dissonance between robots' visual representation and functional capabilities to support HRI (Hegel, 2012). Nonetheless, when robots become more prevalent in retail and service industries, the level of anxiety will most likely lower, and thus increasing the social capability and the physical attractiveness of robots will create an overall positive effect for consumers in the long run. Accordingly, a desirable RSR design is useful in providing a user-friendly environment for HRI and the adoption of RSRs.

Through a focus group and personal interviews, the researcher has also learned that consumers hold two different views about robots. While some people think that robots will significantly contribute to the future of human development and to the robotic automation in many industries, others worry about RSRs' negative social influences such as replacing humans, increasing the unemployment rate, and dominating human society. The automation and the rise of AI will most likely decimate many jobs in manufacturing, retail, service, and education. Retailers are increasingly moving toward online business. As a result, today's retailers also need to come up with an alternative to the brick-and-mortar store. A potential option might be RSRs. To create greater efficiency and profitability, companies that handle large volumes of products, perishable products (groceries), or provide delivery service (e.g., Amazon, Walmart, Target, and Ocado) will ultimately prefer to automate much of their work. These companies will be able to gather more accurate retail data using AI, which eventually will help them accommodate their consumers better, provide personalized service, and make retail stores more engaging and pleasurable. Despite the controversy, the robotic automation in retail and service businesses appears to be inevitable, but comprehensive robotic automation is still a long way out.

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Limitations and Directions for Future Research

The current study has some limitations, which requires a critical interpretation of the findings. First, the researcher collects the data by using an online survey that limits the pool of participants to those with internet access. Because of this web-based survey, the researcher acknowledges the inability to reach challenging consumer groups such as the elderly and consumers who live in remote locations or do not own computers or mobile phones. Thus, the results can be different when using a paper-based survey or a telephone survey. Furthermore, the data are collected from consumer panels residing in the United States. Therefore, the generalizability of the results is restricted to those who live in the United States. Future studies could extend this acceptance model to other countries with different cultural backgrounds.

Given the circumstance that general consumers are mostly unfamiliar with RSRs, the researcher uses video clips as stimuli to inform participants in a realistic scenario. While using the video clips helps participants engage actively in the survey (Petr et al., 2015), the researcher also recognizes a potential media effect coming from using multimedia on participants' responses to the stimuli. While the use of video media is appropriate for the study of RSRs, the video media might generate a more enjoyable and pleasant effect on consumers' overall perception of the content (Kozma, 1994).

The participants' median age is 41, which is comparably higher than the US national median age of 37.7 years in 2015 (Statista, 2017b). Thus, the researcher recognizes the drawback from using a sample that represents an older adult population (3.3 years older) than the average US consumer age group. Further, the study participants' median annual household income is between \$60,000 - \$79,999 that is also higher than the US median household income of \$56,516 in 2015 (Statista, 2017a). The household income rises as the age of the participant increases. The household income also increases considerably as the educational attainment of the participant rises. When the participants' age and their education level are higher, their technology acceptance and familiarity with robots might be different from the younger people or people with less education (Porter & Donthu, 2006). Although achieving the seamless demographic mixture of participants is not easy in a survey, future studies should have tighter control of the distribution of the survey to obtain a more balanced sample that represents general US consumer groups in age, income, and education.

The results also show that the attitudes toward HRI display poor discriminant validity from usefulness, anticipated service quality, and acceptance. Although the attitudes toward HRI are a conceptually different construct from these variables (Davis, 1989; Davis et al., 1989; Lee & Lin, 2005; Nomura & Kanda, 2003; Nomura et al., 2008), they are tightly related to each other in the empirical data analysis. Although the researcher inspects the item cross-loadings and deletes indiscriminate items during the data analysis, further item analyses might help to reduce the severity of the discriminant validity problems using several approaches: 1) improving AVEs (e.g., by dropping items with the large measurement error variance), 2) re-assessing cross-loadings, or 3) merging the problematic constructs with high correlations after carefully scrutinizing the scales in detail (Hair et al., 2006; Henseler, Ringle, & Sarstedt, 2015). Future studies should consider re-evaluate the measurement instrument of this study to determine whether all the constructs domain facets have been properly captured. This discriminant validity assessment should be conducted objectively by at least two researchers (Henseler et al., 2015).

The researcher uses a type of humanlike robot called "Pepper" in the video stimuli. To investigate a more accurate effect from appearance, testing several types of robots could provide more extensive evidence on consumers' perception of the humanlikeness and attractiveness of

RSRs (Strait et al., 2015). Future studies should consider determining consumers' preference for the aesthetic design of RSRs such as physical structure, shape, color, size, human features (i.e., a face, arms, and legs), speed, voice, and the gender of robots (Beer et al., 2011). Another extension of this study would be having an experiment in a lab to investigate how the RSR's social behavior, functional features, and appearance influence users' feedbacks. Users' reactions to the robots can be videotaped and they complete a survey questionnaire about their experiences after the experiment. While the current study uses hypothetical video scenario and measures the attitudinal HRI and the behavioral intention, a lab-based experiment could certainly capture the actual HRI experiences and record the users' any behavioral change that may occur during the experiment. Lastly, consumers' preconceived belief of how RSRs should look and behave will change gradually through further technological alteration. Once robotic technologies become widespread and advanced to make RSRs more capable, intelligent, humanlike, natural, and socially interactive, then consumers will be more familiar with robots and will have less anxiety toward robots. With this rapid change in robot technologies, the validation of the acceptance model will require future research in terms of consumers' changing perceptions and individual motivations to use a robot that direct the adoption process.

Conclusion

With the recent advancement of robotics and AI technologies, today's robots offer a variety of intelligent capabilities, and retailers are progressively testing the potential use of robots in sales and service environments. Using the CASA and domestication theories as underlying theoretical frameworks, this study builds a RSR acceptance model focused on attitudinal HRI. The model opens future avenues for research on technology acceptance models concerning robots. Based on the findings, the study asserts that the facilitating factors of HRI are usefulness, social capability, and the appearance. These factors form consumers' attitudes toward HRI and these attitudes in turn affect the anticipation of service quality and the acceptance of the RSRs. The expected quality of service tends to strongly influence the extent of the acceptance. Moreover, the study finds that the pre-existing anxiety toward robots weakens the relationship between the social capability and the appearance of a RSR and attitudes toward HRI.

This study contributes to the literature on the CASA and domestication theories and to the human-computer interaction that involve robots or artificial intelligence. By considering social capability, humanness, intelligence, and the appearance of robots, the researcher believes that the model of RSR acceptance will provide new insights into psychological, social, and behavioral principles that guide the commercialization of robots. The researcher hopes that this acceptance model will help retailers and marketing professionals formulate strategies for effective HRI and RSR adoption in their businesses.

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APPENDICES

APPENDIX A
HUMAN SUBJECT EXEMPTION APPROVAL FORMS

THE UNIVERSITY OF
TENNESSEE
KNOXVILLE

Re: UTK IRB-16-03046-XP
Study Title: Retail Service Robot Acceptance and Human-Robot Interaction (HRI)

Dear So Young Song:

The UTK Institutional Review Board (IRB) reviewed your application for the above referenced project. It determined that your application is eligible for expedited review under 45 CFR 46.110(b)(1), categories (6) and (7). The IRB has reviewed these materials and determined that they do comply with proper consideration for the rights and welfare of human subjects and the regulatory requirements for the protection of human subjects. Therefore, this letter constitutes full approval by the IRB of your application (version 1.1) as submitted, including:

Signed Informed Consent_Focus Group Interview_REVISED (English) - (Version 1.0)
Signed Informed Consent_Face-to-face Interviews_REVISED (English) - (Version 1.0)
Informed Consent Statment_Pretest_REVISED (English) - (Version 1.0)
Informed Consent Statement_Pilot test_REVISED (English) - (Version 1.0)
Informed Consent Statement_Main test_REVISED (English) - (Version 1.0)
Email Invitation for Pretest - (Version 1.0)
Email Invitation_Face-to-face In-depth Interview - (Version 1.0)
Email Invitation_Focus Group Interview - (Version 1.0)
Pre-test_Survey Scale Items_Retail Service Robot - (Version 1.0)
Pilot Test_Survey Scale Items_Retail Service Robot - (Version 1.0)
Main Test_Survey Scale Items_Retail Service Robot - (Version 1.0)
Video setting Link list_Retail Service Robot - (Version 1.0)
Focus Group_Interview_Question Script - (Version 1.0)
Face-to-face in-depth interview_Question Script - (Version 1.0)

Institutional Review Board | Office of Research & Engagement
1534 White Avenue Knoxville, TN 37996-1529
865-974-7697 865-974-7400 fax irb.utk.edu

In accord with 45 CFR 46.116(d), informed consent is waived for participants involved in the Pretest, Pilot Test, and Main Test. The requirement to secure a signed consent form is waived under 45 CFR 46.117(c)(2). Willingness of the subject to participate will constitute adequate documentation of consent.

In the event that subjects are to be recruited using solicitation materials, such as brochures, posters, web-based advertisements, etc., these materials must receive prior approval of the IRB. Any revisions in the approved application must also be submitted to and approved by the IRB prior to implementation. In addition, you are responsible for reporting any unanticipated serious adverse events or other problems involving risks to subjects or others in the manner required by the local IRB policy.

Finally, re-approval of your project is required by the IRB in accord with the conditions specified above. You may not continue the research study beyond the time or other limits specified unless you obtain prior written approval of the IRB.

Sincerely,

Colleen P. Gilrane

Colleen P. Gilrane, Ph.D.
Chair

Institutional Review Board | Office of Research & Engagement
1534 White Avenue Knoxville, TN 37996-1529
865-974-7697 865-974-7400 fax irb.utk.edu

THE UNIVERSITY OF TENNESSEE KNOXVILLE

Exp211 Rev Approval (No Provisos)
February 28, 2017

So Young Song,
UTK - Coll of Education, Hlth, & Human - Retail, Hospitality, and Tourism Mgmt

Re: UTK IRB-16-03046-XP
Study Title: Retail Service Robot Acceptance and Human-Robot Interaction (HRI)

Dear Dr. Song:

The UTK Institutional Review Board (IRB) reviewed your application for **revision** of your previously approved project, referenced above.

The IRB determined that your application is eligible for **expedited** review under 45 CFR 46.110(b)(2). The following revisions were approved as complying with proper consideration of the rights and welfare of human subjects and the regulatory requirements for the protection of human subjects:

Approved Revisions to Study:
Revise Video Links for Main Test
Revised Main Test Survey
Increase participant recruitment from a total of 1714 total participants to 4550 participants (analysis requires a larger sample size)

- Main Test - from 1000 participants to 4000
- Face-to-Face Interviews - from 6 participants to 20
- Focus Group - from 8 participants to 30

Approved Revised/New Study Documents:
IRB Application v1.2
Revise Video Link for Main Test Retail Service Robot v2.0
Revised Main Test Survey v3.0

Approval does not alter the expiration date of this project, which is 06/02/2017.

Institutional Review Board | Office of Research & Engagement
1534 White Avenue Knoxville, TN 37996-1529
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In the event that subjects are to be recruited using solicitation materials, such as brochures, posters, web-based advertisements, etc., these materials must receive prior approval of the IRB. Any revisions in the approved application must also be submitted to and approved by the IRB prior to implementation. In addition, you are responsible for reporting any unanticipated serious adverse events or other problems involving risks to subjects or others in the manner required by the local IRB policy.

Finally, **re-approval** of your project is required by the IRB in accord with the conditions specified above. You may not continue the research study beyond the time or other limits specified unless you obtain prior written approval of the IRB.

Sincerely,

Colleen P. Gilrane

Colleen P. Gilrane, Ph.D.
Chair

APPENDIX B
PRETEST 1. SURVEY

Pretest 1. Survey Questions

You will now watch several videos of retail service robots. Imagine that you are in a retail store, employing robots as sales or service staffs. Please provide us your overall opinion of the retail service robots in the videos.

Functionality

Think about the retail service robots in the short videos. To what extent do you agree with the following statement?

		Strongly Disagree						Strongly Agree
1	Using the retail service robot would require a lot of my mental effort.	1	2	3	4	5	6	7
2	It would be difficult to shop without the retail service robot.	1	2	3	4	5	6	7
3	The retail service robot seems to be responsible.	1	2	3	4	5	6	7
4	Using the retail service robot would enhance my effectiveness in shopping.	1	2	3	4	5	6	7

Social Capability

Think about the retail service robots in the short videos. To what extent do you agree with the following statement?

		Strongly Disagree						Strongly Agree
5	The retail service robot does not seem to interrupt when the customer is talking.	1	2	3	4	5	6	7
6	The retail service robot seems to remember the detailed information about the customer's question, if any.	1	2	3	4	5	6	7
7	The retail service robot appears to display appropriate expression to the customer's confusion or contentment.	1	2	3	4	5	6	7
8	The retail service robot seems to show signs of thinking before answering questions or fulfilling the customer's request.	1	2	3	4	5	6	7

Appearance

Think about the retail service robots in the short videos. To what extent do you agree with the following statement?

		Strongly Disagree						Strongly Agree
9	The retail service robot looks lifelike.	1	2	3	4	5	6	7
10	The retail service robot looks familiar.	1	2	3	4	5	6	7
11	The motion of the retail service robot seems to be predictable.	1	2	3	4	5	6	7

Attitudinal Human-Robot Interaction (HRI)

Think about the retail service robots in the short videos. To what extent do you agree with the following statement?

		Strongly Disagree						Strongly Agree
12	I would make an interpersonal interaction with the retail service robot.	1	2	3	4	5	6	7
13	If the retail service robots had emotions, I would interact with them more.	1	2	3	4	5	6	7
14	If the retail service robots had emotions, I would be more familiar with them.	1	2	3	4	5	6	7
15	I would talk to the retail service robot to learn about product knowledge.	1	2	3	4	5	6	7

Retail Service Robot (RSR) Acceptance (Behavioral Intention to Use)

Think about the retail service robots in the short videos. To what extent do you agree with the following statement?

		Strongly Disagree						Strongly Agree
16	Overall, the retail service robot would come up to my expectations of what makes a good retailer.	1	2	3	4	5	6	7

Inhibitor: Anxiety toward Retail Service Robot

Imagine that you are in a retail store, employing a robot as sales or service staff. Assuming that you have an opportunity to use/interact with the retail service robot.
I would feel anxious about….

		Strongly Disagree						Strongly Agree
17	The retail service robot may operate improperly.	1	2	3	4	5	6	7
18	I would be careful about using the retail service robot as it will reduce the confidentiality of my personal information.	1	2	3	4	5	6	7
19	How fast the retail service robot will move.	1	2	3	4	5	6	7
20	Whether I will understand what the retail service robot is talking about.	1	2	3	4	5	6	7

APPENDIX C
VIDEO STIMULI WRITTEN SCRIPTS

Appendix C-1. A script for fashion products (***selected for the main test***).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Pepper:	Hello, welcome to the clothing company.
Pepper:	You can show me the articles, and I will explain which styling details will have visual effect of your appearance.
Pepper:	If you have your customer ID card, please show me so I can offer a personalized text.
Pepper:	I can help you find color and size availability as well.
Pepper:	What can I do for you?
Customer:	Pepper, I have my user ID here.
Pepper:	Alice, welcome back! We have some great new clothing for you.
Customer:	Alright, Pepper, I really like this dress, can you tell me more about it?
Pepper:	This type of wrap dress gives attractive body line to the upper body, with a defined waist, and also gives the visual effect of looking taller.
Pepper:	This dress is made of 50% Rayon, 45% Cotton, 5% Spandex. I recommend dry-clean or hand-wash in cold water with mild detergent and air-dry.
Pepper:	Such wrap-dress style can be stylish and timeless and it will live in your closet year after year.
Pepper:	Based on your full body scan information, can I suggest other styles as well?
Pepper:	How about some color-block dress or white flare dress on my tablet?
Customer:	Hmm…. How about this blue one here?
Pepper:	This color block style emphasizes femininity, and helps elongate heights and look slimmer.
Pepper:	The color-blocking is a popular trend in this season, and is great for corporate wear.
Pepper:	This style is a relaxed-fit dress that allows comfortable movement, especially with premium cotton and Lycra blend.
Pepper:	Currently, size “small” in blue is out of stock in the store, but I can help you order online if you like this dress. Can I help with anything else?

Appendix C-2. A script for fashion products (dropped).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Pepper:	Welcome to VanHarem Shoes Store.
Pepper:	How are you doing?
Customer:	Hello, I'm fine thank you.
Pepper:	How can I help you?
Customer:	I'm looking for high-heeled shoes
Pepper:	You can show me shoe styles you like.
Pepper:	I will explain which styling details will have a visual effect on your appearance.
Pepper:	If you have your customer ID card, please show me so I can offer personalized advice.
Pepper:	I can check the availability of colors and sizes in the store as well.
Pepper:	Can I suggest some styles?
Pepper:	How about these wonderful shoes on my right side?
Pepper:	I also have extra information about this item.
Customer:	Oh, they're looking great!
Pepper:	Would you like to try them on?
Pepper:	Yes, I'd like to try them on.
Pepper:	You'll be contacted by my human sales representative. <whistles>
Human sales Representative:	I can help you; follow me please.
Customer:	I'll try them please.
Customer:	That was quick, thank you for your help!
Pepper:	Would you like to come by VanHarem shoes?
Pepper:	What can I do for you?

Appendix C-3. A script for small kitchen appliance (dropped).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Customer:	Hello.
Pepper:	Hello, please tell me the menu you are interested in.
Customer:	Search your coffee machine
Pepper:	I can show you the perfect coffee machine for you, just by answering my question.
Pepper:	The next question: what kind of coffee do you drink?
Customer:	I want to be spoiled and have freedom to choose according to my mood
Pepper:	I see. For a person like you, I will introduce this very popular machine.
Pepper:	The machine is ‘NESCAFÉ Dolce Gusto’
Pepper:	Wish this machine, you can enjoy delicious orangey coffee easily, just with one push of a button.

Appendix C-4. A script for small kitchen appliance (dropped).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Pepper:	Your 'NESCAFÉ Dolce Gusto' coffee machine is the ultimate coffee maker at the top of the line with extra-large color touch screen and with customized features to make your own. Can I recommend you one?
Pepper:	Hello.
Customer:	Hello. Can you search for a coffee machine for me? I also want to buy some coffee beans.
Pepper:	I see.
Customer:	I am looking for a coffee machine that is easy to use that is also nice to have, some customized features such as making espressos, cappuccinos, or any other variety of coffee drinks.
Pepper:	I can show you the perfect coffee machine for you just by answering my question: what kind of coffee do you drink?
Customer:	I would like dark roasted coffee or an espresso.
Pepper:	I see, for a person like you I will introduce this very popular machine.
Pepper:	The machine is 'NESCAFÉ Dolce Gusto'.
Pepper:	With this machine, you can enjoy delicious orangey coffee easily, just with one push of a button.
Customer:	I like this coffee machine. I like the one touch control panel and simple design. It looks convenient and easy to use.
Pepper:	Thank you for listening to me, it was a pleasure speaking to you.
Pepper:	Please let the store staff know if you would like to purchase the machine.
Customer:	Thank you for your help.

Appendix C-5. A script for technology products (***selected for the main test***).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Pepper:	Hello, welcome to the mobile phone store.
Pepper:	If you have any questions, I can check my data and give you personalized recommendations of our products. I can also help you place orders at my touch screen. What can I do for you?
Customer:	Hello, I need a phone with a large screen and with an awesome camera. Can you explain some features and capabilities of several phones?
Pepper:	Sure, let me check the new products features.
Pepper:	Can I suggest this item? This new phone product has the wide screen with the pure color LCD and has the best camera performance with digital zoom.
Customer:	That is great! The style is important. The battery life is also important.
Pepper:	Those factors are important features to consider when purchasing a new mobile phone. If you find yourself wishing you could zoom in on distant subjects and still get a decent shot, then this is the phone for you. It is the best budget phone you can buy with a premium look and feel, dual camera, and great battery life of 23 hours run time.
Pepper:	If you have your customer ID card, I can check if you're qualified to receive 30% discount on your next purchase. I can help you with the user instruction and cell phone plan. What do you think of this phone?
Customer:	I like that.
Customer:	Thank you for your help!

Appendix C-6. A script for technology products (dropped).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Pepper:	Hello, it's nice to meet you.
Pepper:	Welcome to the mobile phone store. What can I do for you?
Pepper:	I can show you several latest models of smart phone. Are you looking for anything in particular?
Pepper:	If you have your customer ID card, please show me so you can take advantage of membership benefit of discounts on your monthly data plan.
Customer:	Hello, can you explain some features and capabilities of several phones? I want to make sure I am comfortable with the way it looks and the way it feels in my hand. If I buy data bundles that can be shared among my family members, will it be better? I have four family members who use smart phones. Can you recommend one?
Pepper:	Sure! Let me check new product features and new data plan.
Pepper:	Can I suggest this item?
Pepper:	This phone is the best budget phone you can buy, with the best camera performance and with the wide screen. This phone carrier offers a shared family data plan to get the largest discount when you add three people to your family users. What do you think about this phone?
Customer:	That is great, I like that!
Customer:	Thank you for your help.

Appendix C-7. A script for food products (***selected for the main test***).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Customer:	Hi Pepper, I’m starving.
Pepper:	Hello, how are you? Delighted to serve you in Mastercard café. Please pair with your master pass wallet to start ordering.
Pepper:	Nice to meet you Veronica, what would you like to order?
Customer:	Can I have a beef burger?
Pepper:	Sure!
Customer:	Can I add two fries?
Pepper:	Regular or large?
Customer:	Large, please.
Pepper:	Alright, anything else?
Customer:	Orange juice please.
Pepper:	Sure.
Customer:	That’s all.
Pepper:	Great. We have a promotion today. You can get one cheese cake for $2.00. Would you like to add it?
Customer:	How many calories does it have?
Pepper:	Each cheesecake contains 300 calories, 18 grams of fat, 20 grams of carbs, and 4 grams of protein. Would you like to have it?
Customer:	Okay, I’ll have it.
Pepper:	Great, the total amount that will be charged to your card ending in numbers 3721 is 15 dollars and 50 cents. Please say, “approved” to authorize the transaction.
Customer:	Approved.
Pepper:	I’m processing your transaction now.
Pepper:	Your transaction is completed; please collect your meal at the counter. Enjoy!
Customer:	Thanks Pepper!

Appendix C-8. A script for food products (dropped).

Narrator	Script
Narrator:	A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions.
Pepper:	Hello, nice to meet you.
Customer:	Hello, nice to meet you.
Pepper:	May I take your order?
Customer:	I would like to order chicken alfredo pasta, breadsticks and a garden salad. Can you bring me marinara dipping sauce?
Pepper:	Sure.
Pepper:	All right, anything else?
Customer:	For desserts, I'm thinking to order cinnamon apple pie, four pieces. How many calories are in an apple pie?
Pepper:	Let me check my data. When I connect to the cloud, I have the ability to pull and listen information from the Internet. One slice contains 180 calories; 57% of the calories from carbohydrates, 42% from fat and 3% from protein. Would you like to add it?
Customer:	Yes, I'd like to order them. How much will it be in total?
Pepper:	The total amount that will be charged to your card ending in numbers 3721 is 23 dollars and 50 cents. I am processing your transaction now.
Customer:	Can I rate this restaurant or service?
Pepper:	Sure, I am here to get your opinion. Please let me know if you need anything else.
Customer:	Thank you for your help Pepper!

APPENDIX D
MAIN STUDY SURVEY

Section 1. Survey Introduction and a Screen Question

Dear participant,
You are invited to participate in a study concerning retail service robot and consumers' attitudes toward Human-Robot Interaction (HRI), which is being conducted by researchers in the Department of Retail, Hospitality, and Tourism Management at the University of Tennessee. If you agree to participate in this study, you will view a short video regarding a retail service robot and will be asked to respond to a questionnaire which will take about 15 minutes to complete. You must be 18 years or older to participate. Your participation in this study is voluntary; you may decline to participate without penalty. If you have any questions concerning your rights as a participant, you may contact Campus Institutional Review Board (IRB) at utkirb@utk.edu or (865) 974-7697. If you have any questions regarding the study or the procedures, you may contact the researcher, So Young Song, at ssong9@vols.utk.edu, and 865-974-2141 or the faculty advisor, Dr. Youn-Kyung Kim at ykim13@utk.edu, and 865-974-1025. Thank you.

RISKS
There are no foreseeable risks for participating in this study other than those encountered in every day. Your name will not be linked to your survey responses. Throughout the procedures, if you feel uncomfortable with any questions or experiences, you may stop participation at any time up until the time the survey is submitted.

BENEFITS
The results of this study may benefit society and retail industry by providing the specific knowledge about the consumers' attitudes and behavioral intention toward the retail service robots. Understanding robot acceptance is a critical step in ensuring that service robots adopted for the retail industry, education, and elderly care reach their full potential.

CONFIDENTIALITY
The information in the study records will be kept confidential. Data will be stored securely and will be made available only to persons conducting the study. No reference will be made in oral or written reports which could link participants to the study.

COMPENSATION (eRewards) The payment/compensation (survey incentive of e-Rewards currency) for your survey participation will be issued after the completion of the survey by the marketing research firm (eRewards).Your e-Rewards account will be credited within 48 hours of completion.

CONSENT
I have read the above information. Clicking on the button to continue and completing the survey (questionnaire) constitutes my consent to participate.

Screen Question
What is your age? ______ years

Section 2. Random-Ordered Survey Questions

A retail service robot is an in-store customer service robot with artificial intelligence to help customers in navigating a store, finding products and information, and completing purchase transactions. To date, retail service robots can speak multiple languages and move like people.

If you face the retail service robot in daily life, such as in stores, restaurants, and hotels, to what extent do you agree or disagree with the following statement regarding the robots?

Pre-existing Anxiety Toward Robots

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I would feel anxious about whether the retail service robot might talk about irrelevant things in the middle of a conversation.	○	○	○	○	○	○	○
I would feel anxious about whether the retail service robot might not be flexible in following the direction of our conversation.	○	○	○	○	○	○	○
I would feel anxious about whether the retail service robot might understand difficult conversation topics.	○	○	○	○	○	○	○
I would feel anxious about how I should talk to the retail service robot.	○	○	○	○	○	○	○
I would feel anxious about whether I would understand what the retail service robot is talking about.	○	○	○	○	○	○	○
I fear that using a retail service robot would reduce the confidentiality of my personal information.	○	○	○	○	○	○	○
Using the retail service robot would infringe on my privacy.	○	○	○	○	○	○	○

Now, you will be prompted to watch a video clip of a retail service robot. “Pepper”, a sales/service robot, plays the leading role in this video clip. After watching it, please give us your opinions about the retail service robot in the video clip. Please study the video clip thoroughly.

[A Video Clip Presented Here]

Video Fashion A.

The <u>"NEXT" button</u> will appear right <u>AFTER you finish viewing</u> the video clip.

- Note: The participants are randomly assigned to a version of the three video clips (sequentially) followed by questionnaires.

Fashion	**Technology**	**Food**
		
Run time: 2 mins 03 secs	Run time: 1 min 38 secs	Run time: 1 min 37 secs

Imagine that you are in a retail or service store that employs robots as sales and service associates. Think about the retail service robot in the video clips. To what extent do you agree with the following statements?

Usefulness

Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The retail service robot would be useful.							
The retail service robot would address my shopping needs.							
Using the retail service robot would save me time.							
It would be easy to shop with the retail service robot.							
Using the retail service robot would improve my shopping ability.							
Using the retail service robot would enhance my effectiveness during shopping.							

Social capability

Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The retail service robot appears to be competent.							
The retail service robot seems to be knowledgeable.							
The retail service robot seems to be responsible.							
The retail service robot looks sensible.							
The retail service robot appears to listen attentively.							

The retail service robot appears to say appropriate things.							
The retail service robot listens without interrupting when the customer is talking.							
The retail service robot seems to remember the detailed information about the customer's questions.							
The retail service robot appears to be polite.							

Appearance

Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
The retail service robot looks natural.							
The retail service robot appears humanlike.							
The voice of the retail service robot is humanlike.							
The retail service robot moves in a humanlike way.							
The retail service robot is attractive.							
The retail service robot looks visually appealing.							
The retail service robot is good looking.							
The retail service robot has a good appearance.							

Assume that you have an opportunity to interact with the retail service robot in a retail or service store. To what extent do you agree with the following statements?

Attitudes toward HRI

Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I would feel relaxed talking with the retail service robots.							
I would feel comforted being with the retail service robots that appear to have emotions.							
I would enjoy interacting with retail service robots.							
I would feel pleasure having a conversation with retail service robots.							
Talking to the retail service robot would help me learn about a product.							
Using the retail service robot would be a good way to do research with new products.							
Using the retail service robot would help me learn about useful product information.							

Again, imagine that you are in a retail or service store that employs robots as sales and service associates. Assume that you have an opportunity to use the retail service robot in the video clip. To what extent do you agree with the following statements?

Anticipated service quality

Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
My overall opinion of the services provided by the retail service robot is very good.							
Overall, I would be pleased with the services provided by the retail service robot.							
Overall, the service quality of the retail service robot is excellent.							
Overall, the retail service robot would meet my expectations of what makes a good retailer.							

Retail service robot acceptance

Item	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I intend to use the retail service robot in the future.							
I predict I would use the retail service robot in the future.							
I plan to use the retail service robot in the future.							
I am likely to use the retail service robot in the future.							

Section 3: Demographical Questions

The following statements are regarding your individual characteristics. Your answers will be used only for the descriptive purpose.

What is your gender?

- Male
- Female

Which of the following best describes your racial or ethnic identification?

- African-American
- Caucasian
- Native American
- Asian or Pacific Islander
- Hispanic or Latino
- Other (**Please specify**)

In which state do you currently reside?

(Selection from 50 States, D.C. and Puerto Rico)

What is your marital status?

- Married
- Single, never married
- Separated, divorced, or widowed
- Other (**Please specify**)

What was your approximated TOTAL HOUSEHOLD INCOME last year (before tax)?

- Less than $20,000
- $20,000-39,999
- $40,000-59,999
- $60,000-79,999
- $80,000-99,999
- $100,000-119,999
- $120,000-139,999
- $140,000-159,999
- $160,000 or more
- I prefer not to answer

What is the highest level of education you have completed?

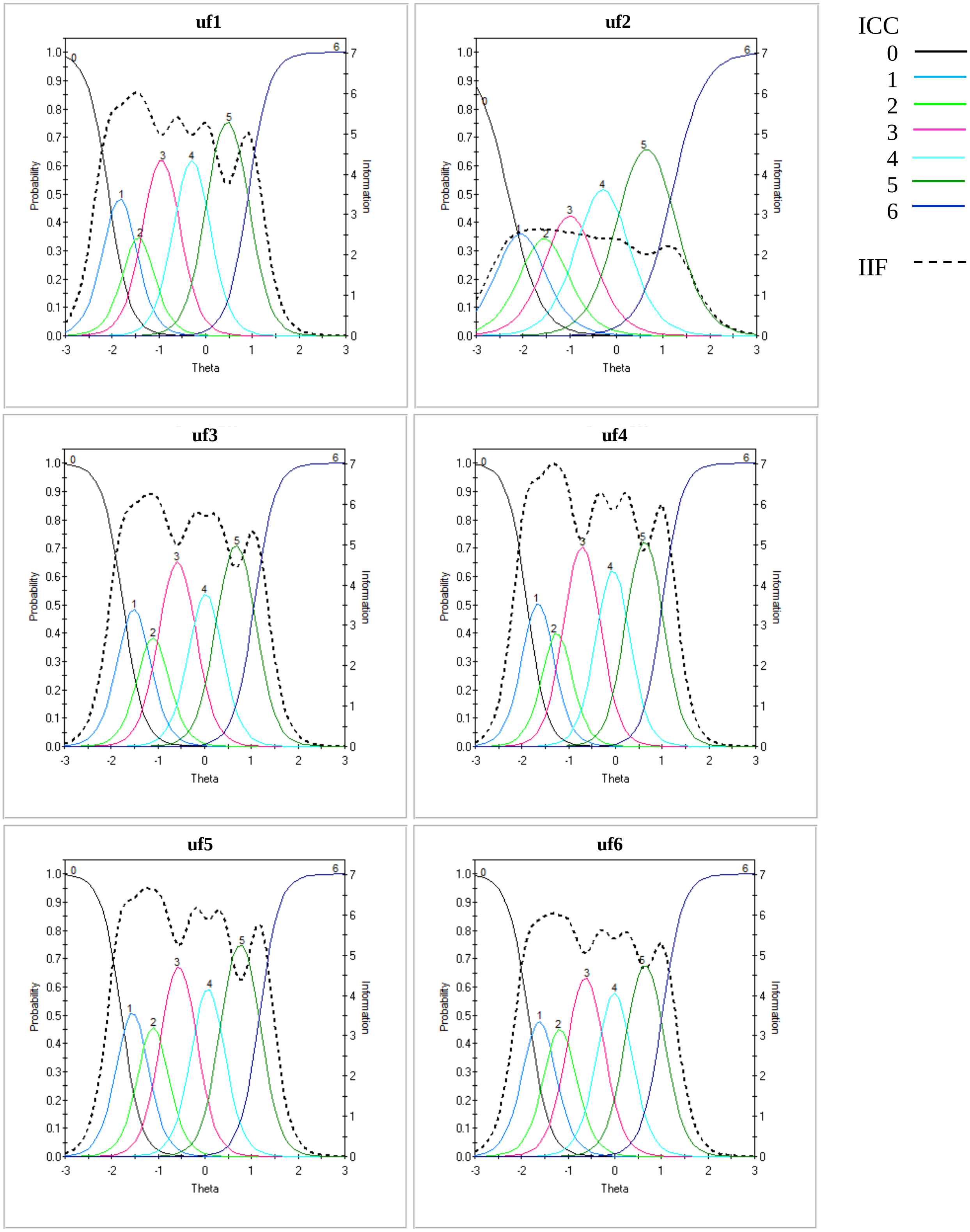
- Less than high school degree
- High school graduate (high school diploma or equivalent including GED)
- Associate degree (community college, technical school, two-year college)
- Bachelor's degree
- Graduate degree (Master's, MBA, or doctoral)
- Other (**Please specify**)

Which best describes your work status?

- Employed (work full-time and/or part-time)
- Student and not working
- Unemployed
- Retired
- Homemaker
- Other **(Please specify)**

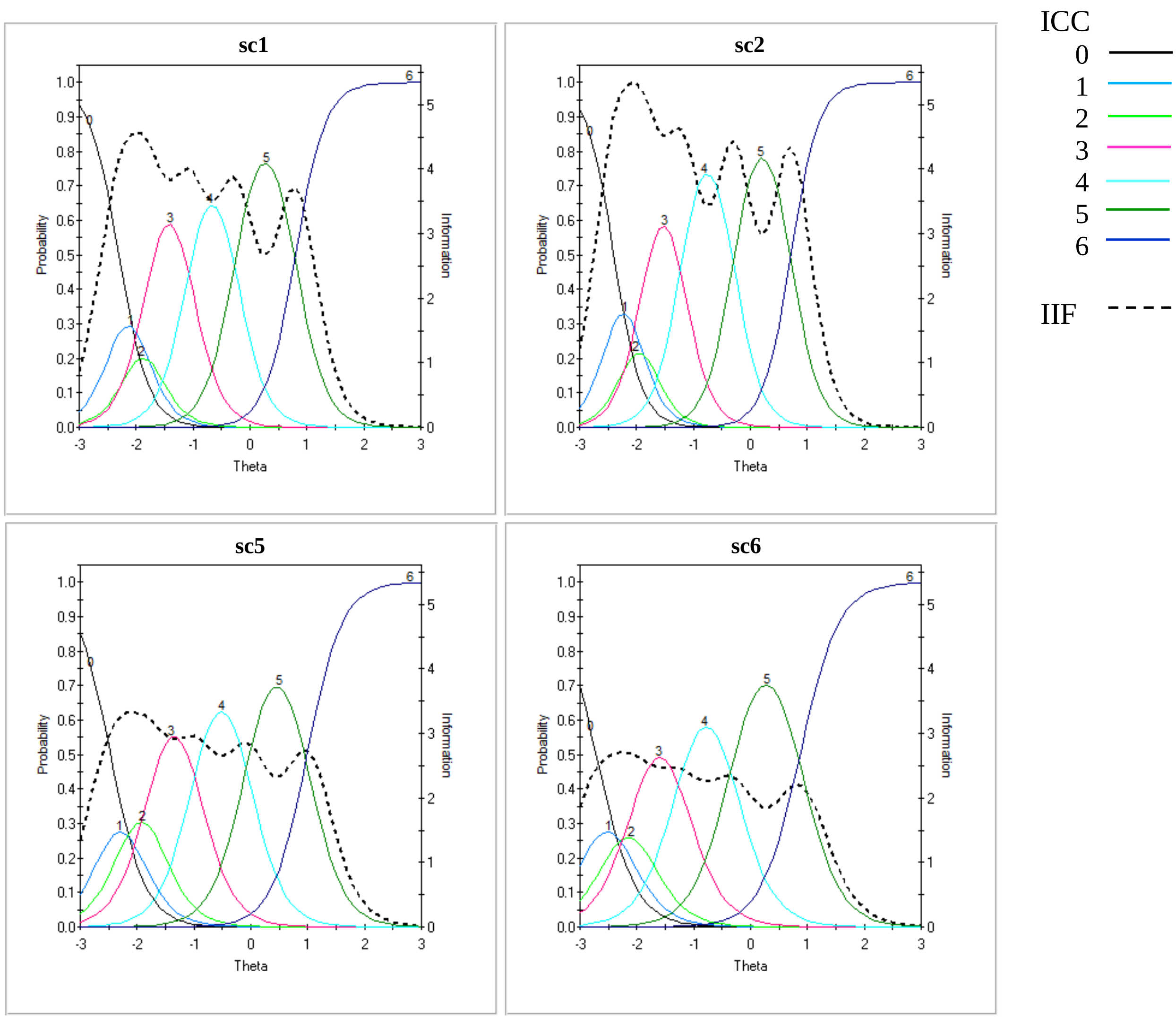
APPENDIX E
ITEM CHARACTERISTIC CURVE (ICC) & ITEM INFORMATION FUNCTIONS (IIF)

Appendix E-1. Usefulness IRT plot.
Item characteristic curve (ICC) and item information functions (IIF).

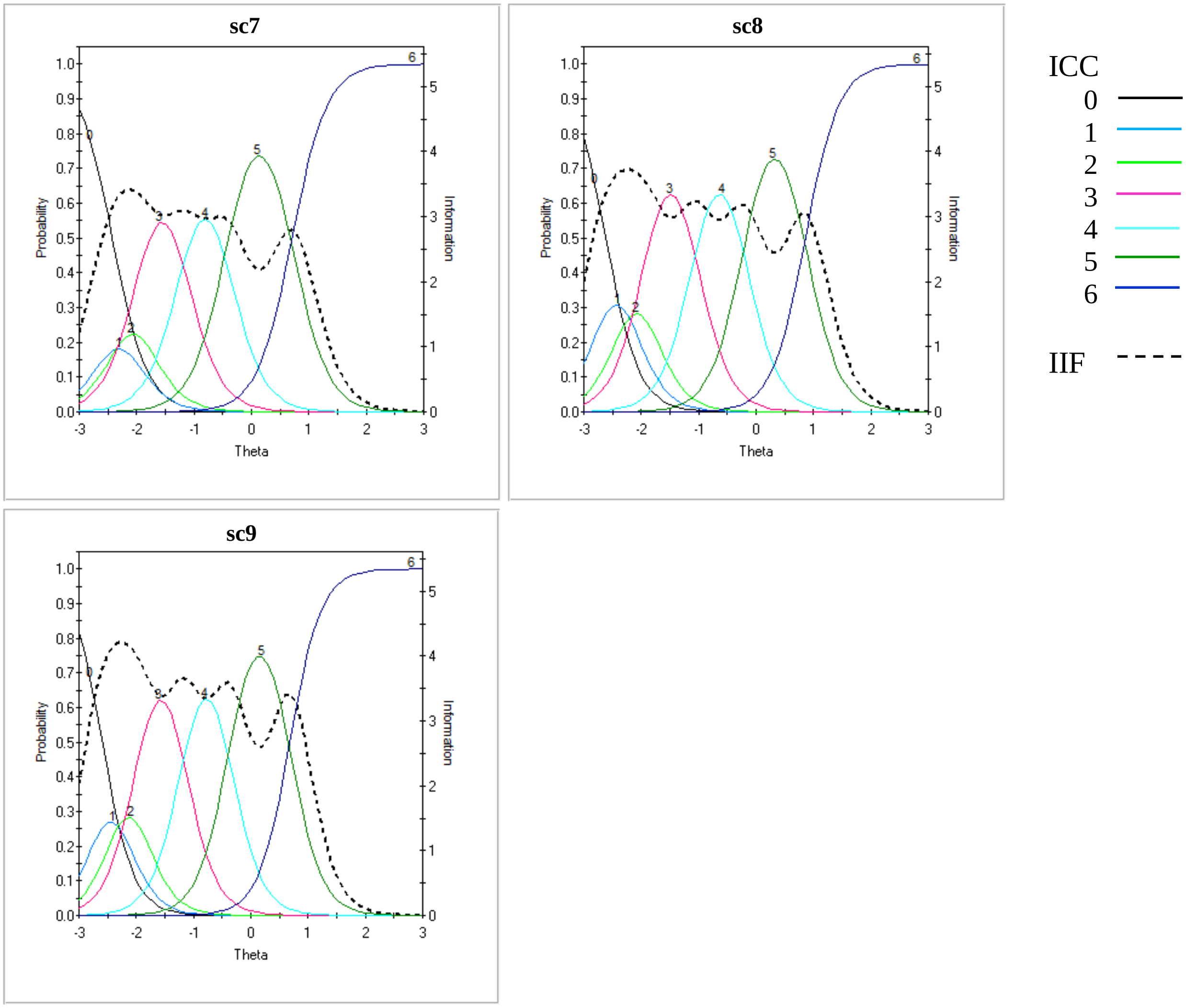


Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

Appendix E-2. Social capability IRT plot.
Item characteristic curve (ICC) and item information functions (IIF).

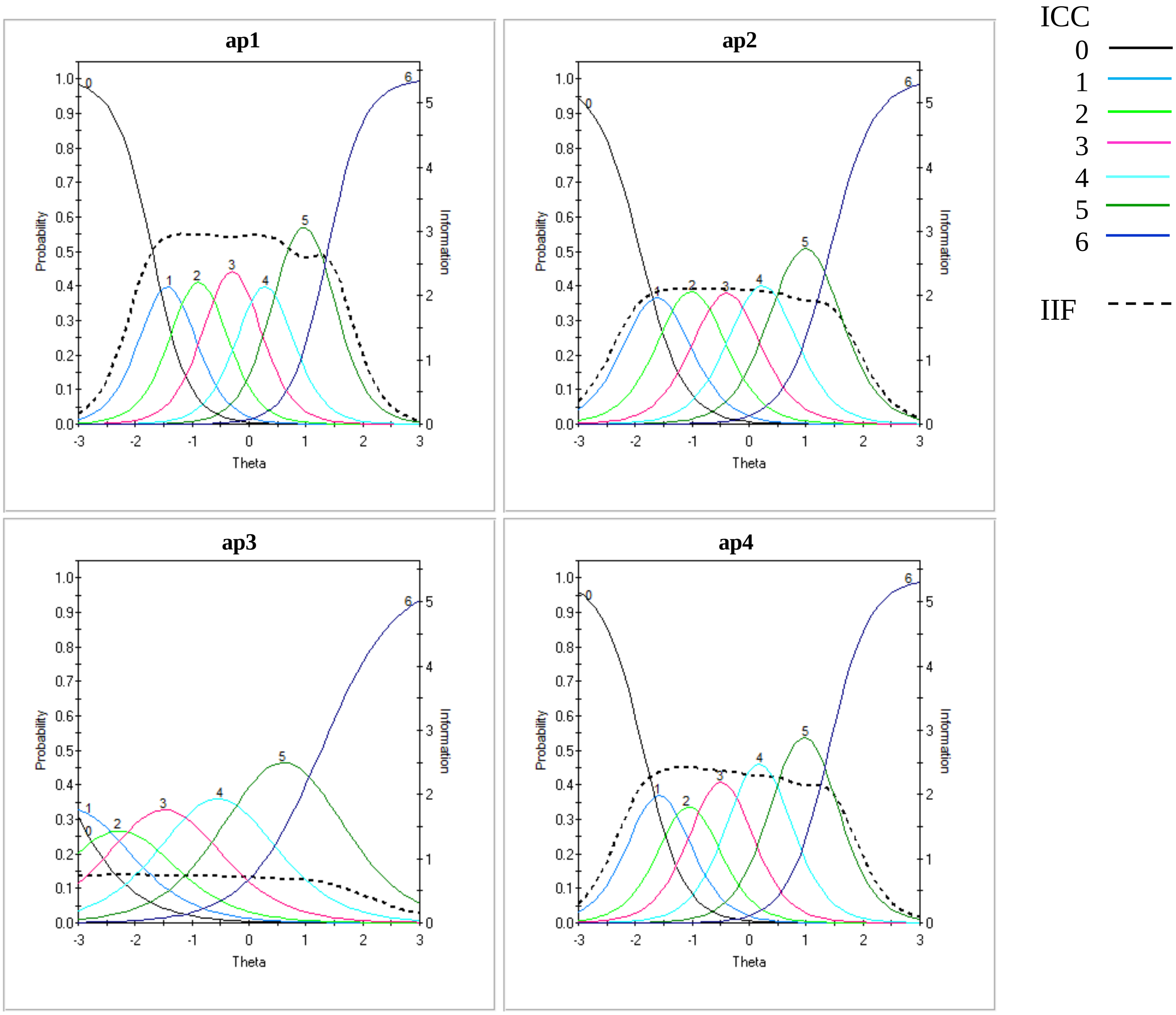


Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

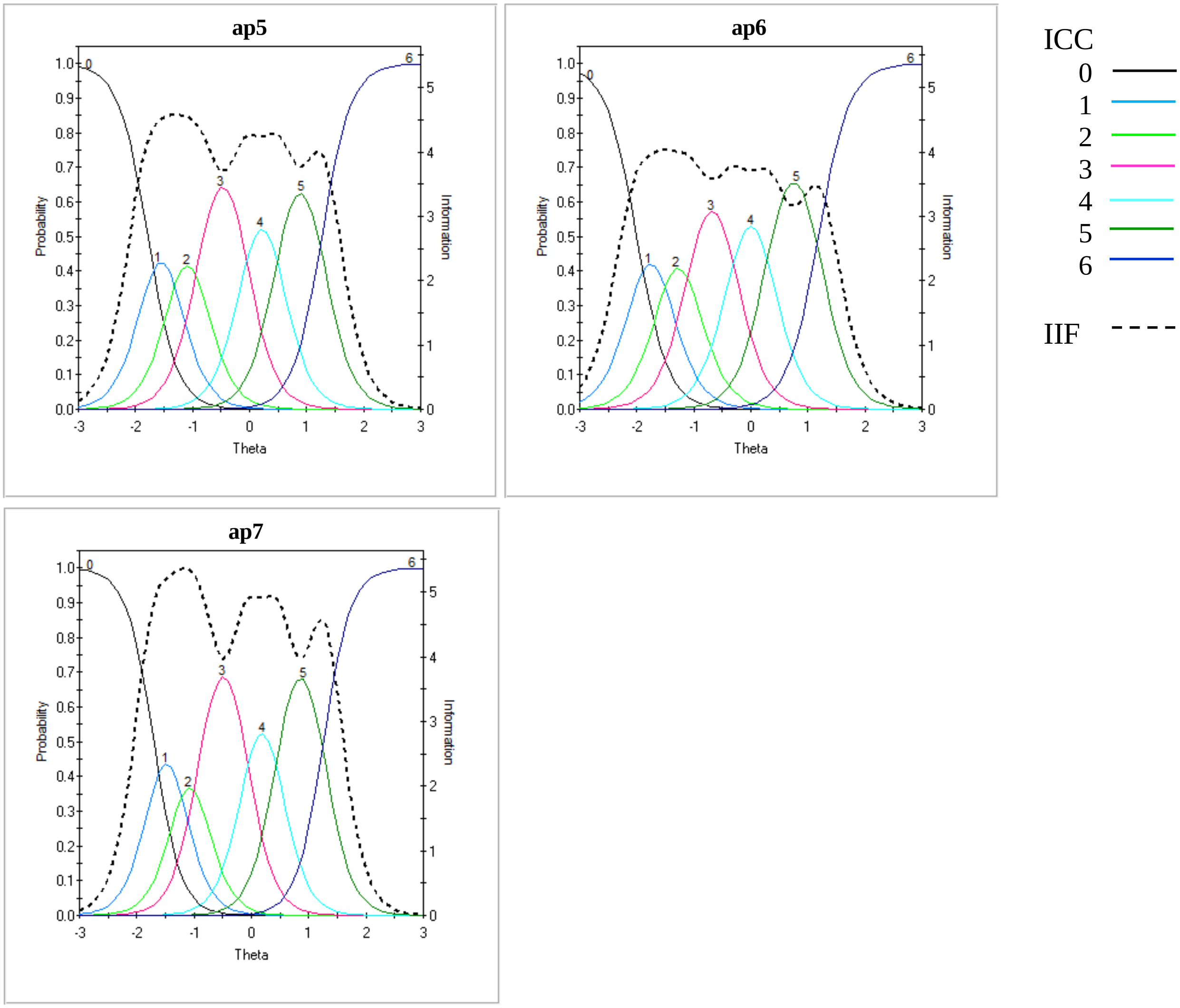


Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

Appendix E-3. Appearance IRT plot.
Item characteristic curve (ICC) and item information functions (IIF).

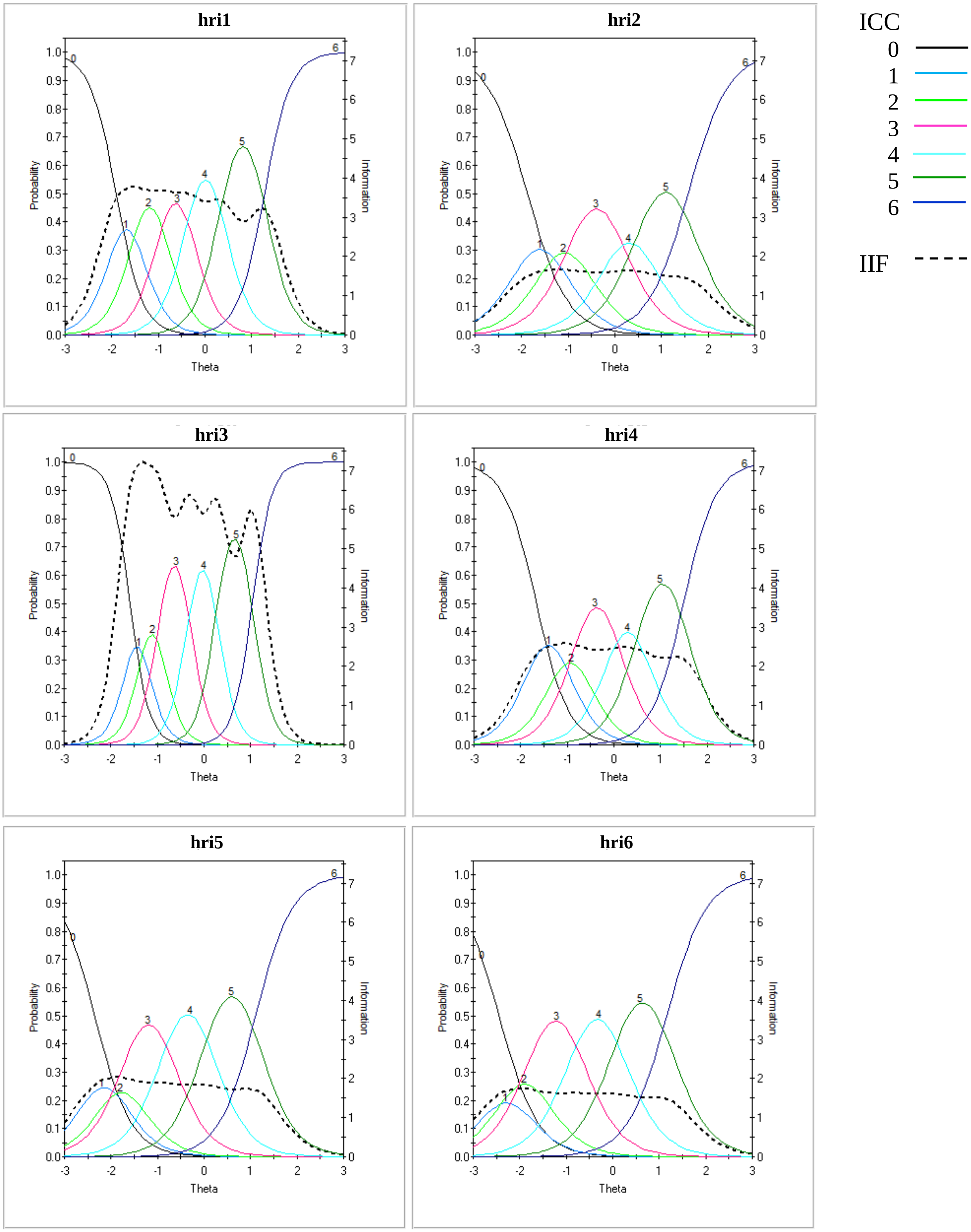


Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.



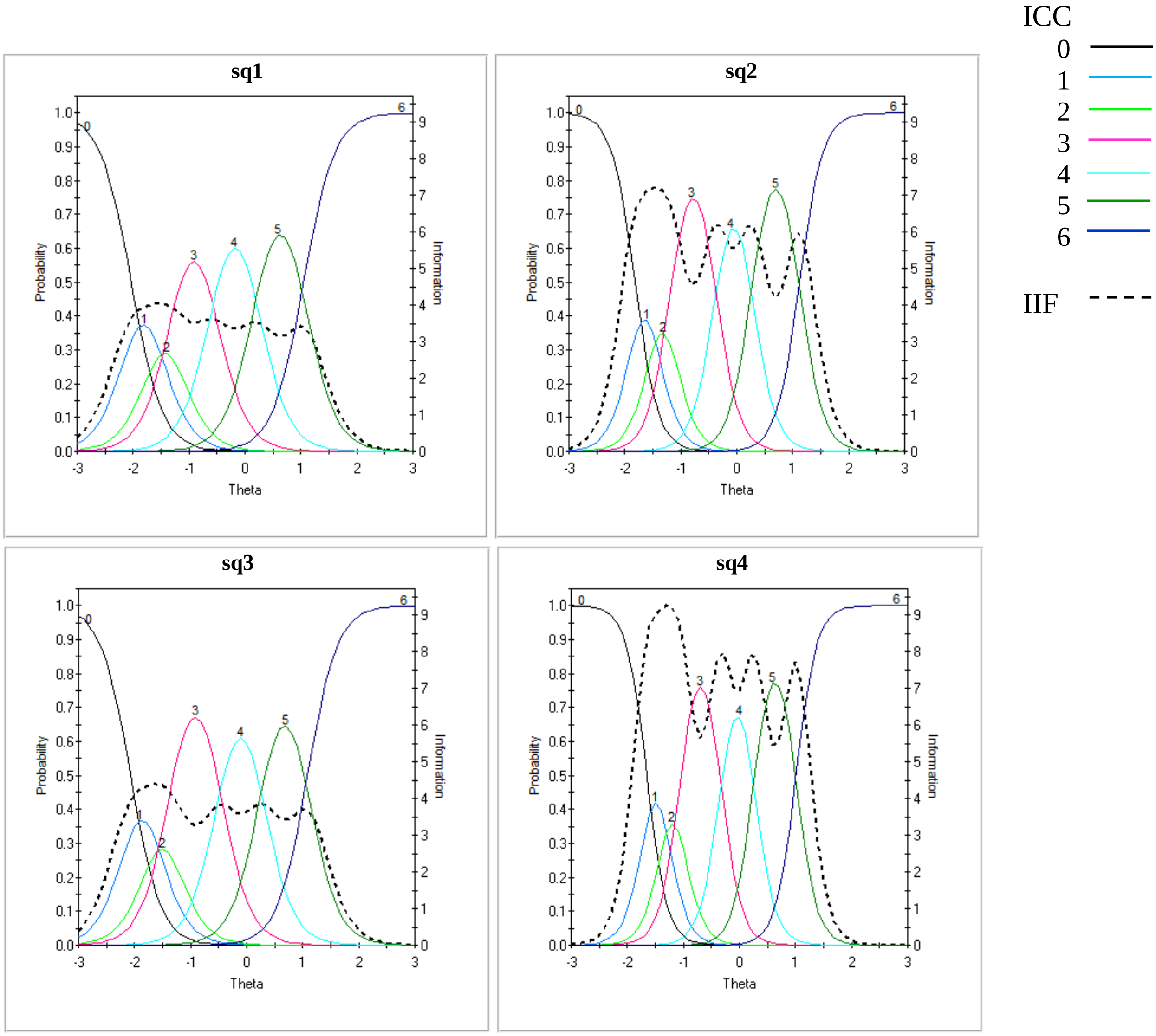
Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

Appendix E-4. Attitudes toward HRI IRT plot.
Item characteristic curve (ICC) and item information functions (IIF).



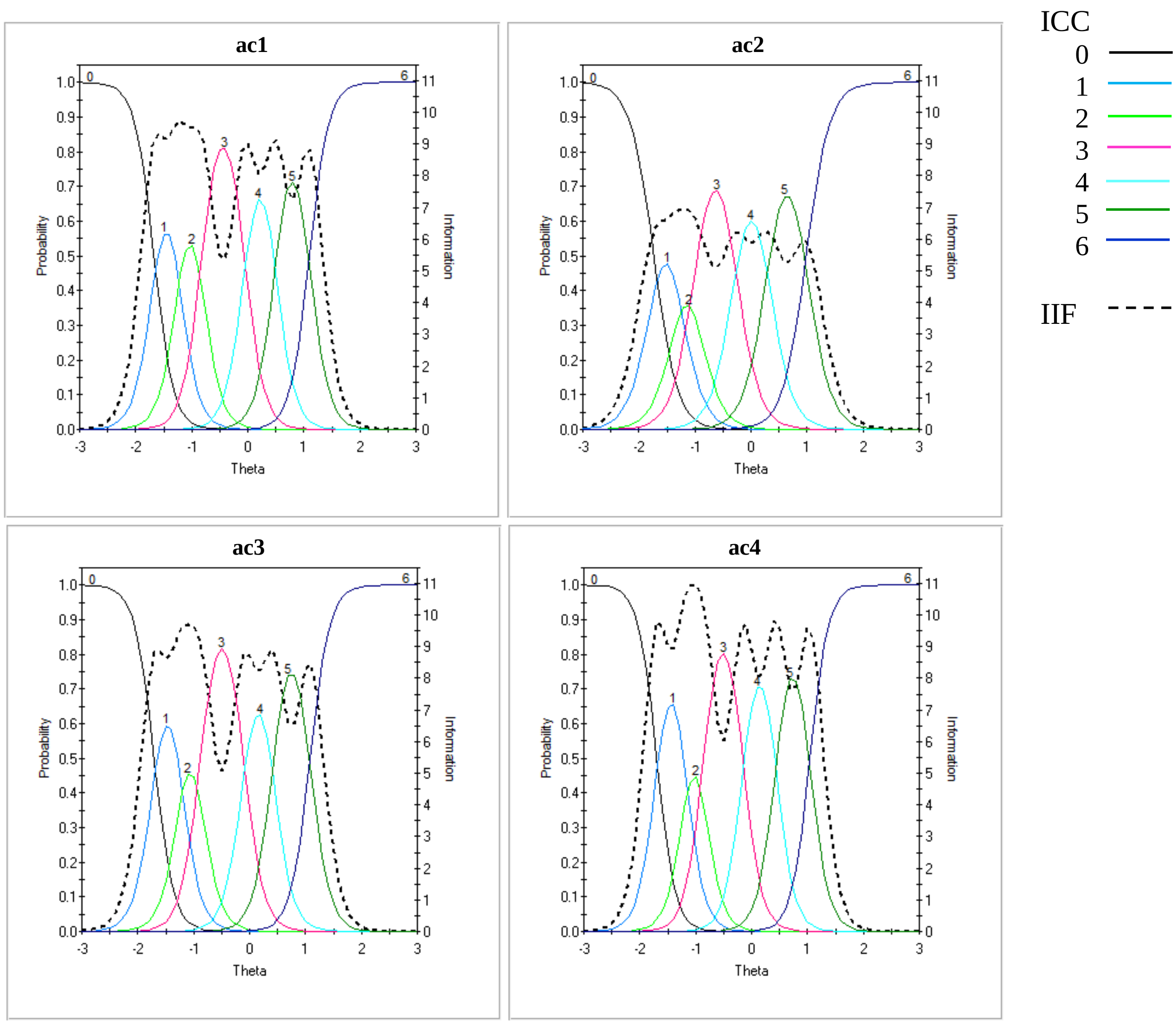
Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

Appendix E-5. Anticipated service quality IRT plot.
Item characteristic curve (ICC) and item information functions (IIF).



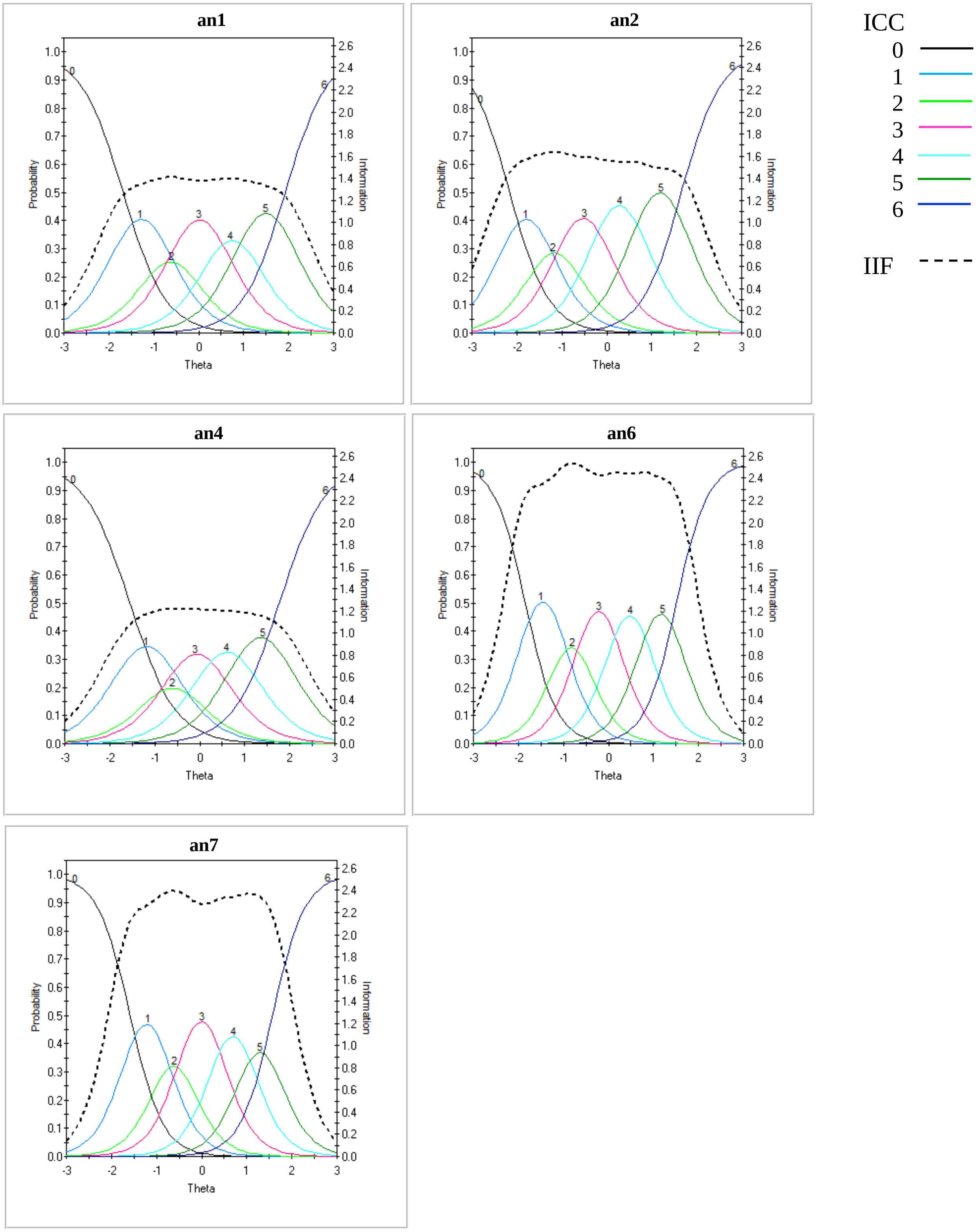
Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

Appendix E-6. Intention to use IRT plot.
Item characteristic curve (ICC) and item information functions (IIF).



Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

Appendix E-7. Anxiety toward robots IRT plot.
Item characteristic curve (ICC) and item information functions (IIF).



Note. The a_i and b_i parameters determine the specific location and shape of ICC curve.

VITA

So Young Song was born in Seoul, the Republic of Korea. In August of 2017, she is expected to earn her PhD in Retail, Hospitality, and Tourism Management from the University of Tennessee, Knoxville, with a concentration in Retail and Consumer Sciences and a Statistics minor. During her doctoral study and teaching assistantship, she taught a course on *Product Development* and co-taught lab practices for data mining in a course on *Customer Relation Management (CRM) and Retail Analytics*. So Young has published articles in the *Journal of Business Ethics, Personality and Individual Differences,* and the *Journal of Textile and Apparel, Technology and Management.* She has also published her teaching project from the 2016 Rutherford Teaching Challenge that won first place in the *International Textile and Apparel Association (ITAA) Teaching Collection.*

Prior to studying at the University of Tennessee, So Young gained corporate experience in New York working at *New York & Company* (technical design) and *Leeward International Inc.* (apparel sourcing and production). In addition, she did her product development internship at *Liz Claiborne* in New York. She also has overseas working experience in the textile and fashion industries at *Worldwidetex Corp.*, *Suh Yang Trading Co., Ltd*, and *Seong An Co., Ltd* in Seoul, the Republic of Korea.

She holds a Bachelor of Science in Production Management: Fashion Related Industries from the Fashion Institute of Technology, New York, and a Master of Science in Safety Science from Embry-Riddle Aeronautical University, Prescott. She also holds a Bachelor of Fine Arts in Photography and a Master of Business Administration (MBA) in Trade and International Business from Sungkyunkwan University in the Republic of Korea.